Habilitation à Diriger des Recherches

Présentée à

L'Université Paris Est

Par

Christophe SABOURIN

Maître de conférences à l'Université Paris Est Créteil

Systèmes cognitifs artificiels : du concept au développement de comportements intelligents en robotique autonome

Soutenue le 23 mai 2016 devant le jury constitué de:

Rapporteurs :		
	ALAMI Rachid	Directeur de recherche au LAAS, CNRS, Toulouse
	BOUCHAFA Samia	Professeur à l'Université d'Evry Val d'Essonne (UEVE)
	HENAFF Patrick	Professeur à l'Université de Lorraine
Examinateurs :	AMIRAT Yacine	Professeur à l'Université Paris-Est Créteil (UPEC)
	CHATILA Raja	Directeur de recherche à l'ISIR, CNRS, Paris
	GARDA Patrick	Professeur à l'Université Pierre et Marie CURIE (UPMC)
	MADANI Kurosh	Professeur à l'Université Paris-Est Créteil (UPEC)
	SASIADEK Jurek	Professeur à Carleton University

Remerciements

Je remercie chaleureusement Samia Bouchafa, Professeur à l'Université d'Evry Val d'Essonne, ainsi que Rachid Alami, Directeur de Recherche au LAAS, et Patrick Hénaff, Professeur à l'Université de Lorraine, pour l'intérêt qu'ils ont porté à mes travaux de recherche en acceptant d'être rapporteur de ce mémoire.

Je tiens également à adresser mes plus sincères remerciements à Raja Chatila, Directeur de Recherche au CNRS et directeur de l'Institut des Systèmes Intelligents et de Robotique (ISIR), Patrick Garda, Professeur à l'Université Pierre et Marie Curie (UPMC) ainsi que Jurek Sasiadek, Professeur à l'Université Carleton au Canada, qui ont accepté de participer à ce jury.

Je remercie aussi vivement l'ensemble de mes collègues de l'IUT de Sénart-Fontainebleau ainsi que ceux du Laboratoire Images, Signaux et Systèmes Intelligents (LISSI), et plus particulièrement Yacine Amirat, directeur du LISSI, pour ses conseils et son soutien depuis mon arrivée au LISSI.

Je tiens aussi à exprimer ma profonde reconnaissance à Kurosh Madani, Professeur à l'Université Paris-Est Créteil, et responsable de l'équipe SYNAPSE au LISSI. Depuis le début de ma carrière d'enseignant chercheur, il a su me guider et m'a régulièrement encouragé dans la préparation d'une HDR. Son aide m'a été très précieuse.

Enfin, je tiens à dédicacer ce mémoire à mon épouse, Hélène, ainsi qu'à mes enfants Marjorie, Lou et Simon. Malgré mon esprit parfois rêveur, je tiens à leur rappeler que je ne les oublie pas. Ils ont toujours été et ils resteront pour moi une source de bonheur inégalable.

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Organisation du mémoire

Ce mémoire décrit mes activités de recherche réalisées au cours de ces dix dernières années au sein du Laboratoire Images Signaux et Systèmes Intelligents (LISSI) de l'Université Paris Est Créteil. Ce mémoire se décompose en trois grandes parties :

– La première partie correspond à un curriculum vitae détaillé présentant l'ensemble de mon parcours professionnel en tant qu'enseignant et chercheur ainsi qu'un bilan de l'ensemble de ma production scientifique.
– La deuxième partie est consacrée à la présentation plus approfondie de mes activités de recherches qui se sont focalisées sur le développement de systèmes cognitifs artificiels appliqués à la robotique avec des applications dans les domaines de la locomotion bipède, la perception et l'acquisition autonome de connaissances ainsi que les systèmes multi-robots et l'intelligence distribuée.
– Enfin, la troisième partie est une compilation de quatre articles de revue représentatives de l'ensemble de mes travaux de recherches.

I - Partie Administrative

Chapitre 1

Curriculum vitae

Christophe SABOURIN
Né le 28 septembre 1969 (46 ans)
Nationalité Française

1.1 Adresse administrative

Adresse :	IUT Sénart Fontainebleau - Département GEII 36 rue Georges Charpak, 77 567 LIEUSAINT CEDEX
Tel :	Tel : +33 (0)1 64 13 51 83
Email :	christophe.sabourin@u-pec.fr

1.2 Parcours professionnel

Depuis 2005 — Maître de Conférences - Université Paris-Est Créteil

- **Section CNU** : 61
- **Enseignement** : IUT Sénart Fontainebleau - Département GEII
- **Recherche** : Laboratoire Images, Signaux et Systèmes Intelligents (LISSI) - EA 3956

De 1995 à 2005	Enseignant dans le secondaire - Académie Orléans-Tours Lycée St Jean Baptiste de La Salle - Bourges

1.3 Parcours universitaire

2004 Docteur de l'université d'Orléans

Titre de la thèse : Approche bio-inspirée pour le contrôle de la marche dynamique d'un bipède sous-actionné : validation expérimentale sur le robot RABBIT.

Date et lieu de soutenance : Bourges le 29 novembre 2004.

Composition du jury :

- Président du jury : Rachid HARBA Professeur, Polytech Orléans
- Rapporteur : Gabriel ABBA Professeur, ENI de Metz
- Rapporteur : Fethi BEN OUEZDOU Maître de conférences HDR, Université de Versailles
- Examinateur : Christine CHEVALLEREAU Chargée de recherche CNRS, IRCCYN Nantes
- Co-encadrant : Olivier BRUNEAU Maître de conférences, ENSI de Bourges
- Directeur de thèse : Jean-Guy FONTAINE Professeur, ENSI de Bourges

1996	CAPET Génie Electrique option Electrotechnique
1993	DEA Automatique et Génie Informatique (Université de Poitiers)
1992	Maitrise Electronique Electrotechnique Automatique (Université de Poitiers)
1990	DUT Génie Electrique et Informatique Industrielle (Université de Poitiers)

1.4 Responsabilités administratives

1.4.1 Responsabilité nationale

1.4.2 Responsabilités locales

Depuis 2015	Chef du département GEII de l'IUT de Sénart Fontainebleau
2012-2015	Membre élu du Conseil Nationale des Universités (CNU) - Section 61
Depuis 2013	Membre élu du comité scientifique de l'IUT de Sénart Fontainebleau
Depuis 2010	Membre élu du conseil du laboratoire LISSI
Depuis 2008	Membre élu du conseil de département GEII de l'IUT de Sénart Fontainebleau

Chapitre 2

Bilan des activités d'enseignement et de recherche

2.1 Enseignement

Ma carrière d'enseignant peut se scinder en deux grandes périodes. La première concerne mon activité en tant que professeur certifié dans le secondaire au sein d'un lycée technique dans les filières technologiques STI (Sciences et Technologies Industrielles) et BTS électrotechnique. La deuxième période correspond au poste de Maître de Conférences que j'occupe depuis septembre 2005 à l'UPEC au sein du département GEII (Génie Électrique et Informatique Industrielle) de l'IUT de Sénart-Fontainebleau.

2.1.1 Enseignement en lycée (1995-2005)

J'ai commencé ma carrière dans l'enseignement en septembre 1995 dans un lycée technique privé sous contrat d'association de Bourges, premièrement en tant que contractuel, puis comme professeur certifié après l'obtention de mon CAPET en 1996. Au sein de ce lycée, mes activités d'enseignement étaient essentiellement centrées sur la formation technologique d'élèves de première et terminale STI en section Électrotechnique et des étudiants préparant un BTS Électrotechnique. Les cours, aussi bien théoriques que pratiques, dont j'avais la charge, portaient sur les domaines suivants :

- production, transport et distribution de l'énergie électrique,
- électrotechnique et électronique de puissance,
- automatique et informatique industrielle.

Dans le cadre de la formation en BTS, j'ai eu aussi la responsabilité du suivi des étudiants lors des stages de première année ainsi que la supervision de projets industriels réalisés par les étudiants en partenariat avec des entreprises locales. Ces projets, financés généralement par les entreprises, avaient pour but de confronter les étudiants de deuxième année à la réalité industrielle.

Avec en moyenne 18 heures de cours par semaine, ces dix années m'ont ainsi permis d'acquérir une solide expérience pédagogique dans le domaine de la formation technologique.

2.1.2 Enseignement en IUT (depuis 2005)

Depuis 2005, mon poste d'enseignant-chercheur au sein du département GEII de l'IUT de Sénart-Fontainebleau (UPEC) m'a conduit à prendre en charge des cours d'informatique industrielle (programmation de microcontrôleur en langage C/assembleur, LabVIEW, Python, etc). Parallèlement à cette activé d'enseignement en informatique, j'ai aussi eu l'opportunité de développer des cours et projets en relation avec mes activités de recherches : la robotique. Ceci m'a permis d'initier des pratiques pédagogiques innovantes à l'aide de supports matériels comme le drone Parrot ou bien le robot Nao. Je tiens aussi à préciser que la majeure partie de mes cours sont dispensés sous forme de TPs, format qui me semble le mieux adapté quant aux contenus des enseignements dispensés ainsi qu'aux profils des étudiants. Cette activité d'enseignement est répartie sur les deux années de formations du DUT et représente un volume horaire, en moyenne, de 220 heures par an.

Au cours de ces 10 dernières années, les différents modules que j'ai mis en place et dont j'ai, ou j'ai eu, la responsabilité sont :

- Informatique industrielle (Semestre 2) : ce module qui concerne l'ensemble de la promotion de première année (environ 90 d'étudiants) a pour but de former les étudiants à la programmation et la mise en œuvre des microcontrôleurs. Les cours et travaux pratiques de ce module permettent d'aborder l'architecture des microcontrôleurs (plus particulièrement les PICs), la programmation en C, et la gestion des interruptions. Ce module se fait quasi-exclusivement sous la forme de TP (4h de cours magistraux associés à une série de 9 TPs de 4h), et il nécessite la collaboration de plusieurs intervenants extérieurs (en effet, pour 6 groupe TPs, le volume horaire global représente 216h TP).
- MAA-robot (Semestre 2) : ce module « Apprendre Autrement » et mis en place de 2008 à 2013, avait pour objectif d'étudier la programmation en langage évolué (langage C, LabVIEW) de petits robots mobiles virtuels (Webots) ou réels (E-puck, Lego Mindstorms NXT). Ce module de 6 TPs était réalisé en fin

du second semestre de première année, et concernait seulement une partie de la promotion (généralement 2 groupes TPs).
– LabVIEW (Semestre 3) : l'enseignement de LabVIEW permet d'aborder la programmation sous un angle radicalement différent puisque elle est généralement graphique. Ce module de 6 TPs ne se focalise donc pas simplement sur l'instrumentation virtuelle mais aussi sur la structuration des programmes et il permet aux étudiants d'avoir un niveau de connaissance suffisant pour obtenir le CLAD (Certified LabVIEW Associate Developer).
– Parcours SIRO (Semestre 4) : le parcours Systèmes Informatiques et RObotiques (SIRO), qui regroupe 5 modules de 24h, a pour objectifs, premièrement de donner aux étudiants un aperçu des technologies utilisées dans les systèmes embarqués mobiles, et deuxièmement, offrir la possibilité aux étudiants de réaliser des mini-projets. Trois modules de ce parcours sont réservés à un complément de formation en informatique industrielle (langage python, FPGA, développement d'application mobile). Les deux autres modules, dont j'ai la charge, permettent à des petits groupes d'étudiants (généralement 3 ou 4) de réaliser un projet dans le domaine de la robotique comme par exemple le contrôle par Joystick des déplacements d'un robot (drone PAROT, humanoïde NAO). La finalité de ce parcours est donc de renforcer les compétences dans le domaine des systèmes embarqués, mais aussi de développer l'autonomie et l'esprit d'équipe via la gestion de projet.

Bien que mes tâches en enseignement au sein du département GEII reposent sur l'enseignement de l'informatique industrielle, j'attache une grande importance au contexte applicatif qui pour mon cas se focalise sur la robotique. Ceci me permet de faire des liens entre enseignement et recherche et m'a conduit plusieurs fois à recruter en stage des étudiants du département dans le cadre de mes travaux de recherche.

D'autre part, j'assume plusieurs responsabilités pédagogiques et administratives au sein du département :
– de 2010 à 2015, j'ai été responsable des stages du département GEII. Cette activité comprenait la rédaction des conventions de stages, la planification du suivi des étudiants, la gestion de l'évaluation et la planification des soutenances. D'un point de vue quantitatif, le nombre d'étudiants dont je devais assurer le suivi variait entre 50 et 60 par an.
– depuis 2013, je suis aussi responsable de la mobilité internationale. Cette activité m'a notamment amené à développer une première collaboration avec le Cégep de Matane au Québec.
– depuis le 1^{er} septembre 2015, j'ai été nommé chef du département Génie Électrique et Informatique Industrielle.

Enfin, j'interviens aussi depuis plusieurs années au niveau M2 du Master ScTIC (Systèmes complexes, Technologies de l'Information et du Contrôle) de l'UFR de sciences de l'UPEC. Mes cours (une vingtaine d'heures de cours magistral) se focalisent sur la robotique (robotique humanoïde, robotique mobile, perception).

2.2 Recherche

2.2.1 Résumé de mes activités de recherche

La robotique est devenue de nos jours un enjeu économique majeur car les applications sont nombreuses aussi bien dans l'industrie que dans le domaine de la robotique de service. Mais si le siècle précédent a été sans conteste l'ère de la robotique industrielle, le $21^{ème}$ siècle sera certainement celui de la robotique de service. En 2013, les ventes de robots de service professionnel et de service personnel ont augmenté respectivement de 4% et 28% par rapport à 2012. Par ailleurs, on estime que 31 millions d'unités de robots de service personnel seront vendus entre 2014 et 2017 [1]. Par conséquent, la robotique de service destinée à améliorer le quotidien de chaque être humain peut avoir à court terme un impact économique considérable, notamment sur la prise en charge à domicile des personnes en perte d'autonomie. Mais bien qu'il soit possible de concevoir des robots très sophistiqués d'un point de vue mécatronique, comme c'est déjà le cas pour des robots humanoïdes (Asimo, HRP, Nao, etc..), les capacités de ces machines restent très limitées, notamment en ce qui concerne leurs capacités d'adaptation à des environnements dynamiques. Car même dotés d'une certaine autonomie, ces robots sont encore loin d'égaler les performances humaines notamment en terme d'« intelligence ». Le terme intelligence est ici utilisé dans le sens de la définition donnée par « oxford dictionary », à savoir : « capacité à acquérir et utiliser des connaissances et compétences nouvelles ». Un des enjeux de la robotique de ce siècle sera donc de développer des architectures matérielles et logicielles permettant aux robots d'interagir avec leur environnement afin d'assimiler, progressivement, des connaissances et compétences nouvelles. L'idée centrale n'est donc pas de créer un robot immédiatement intelligent, mais plutôt de créer un robot qui, à partir d'un nombre réduit de connaissances initiales (innées), sera capable d'apprendre progressivement des connaissances et compétences nouvelles. Dans ce contexte, les sciences cognitives peuvent apporter des éléments de réponse intéressants en fournissant un cadre théorique interdisciplinaire qui regroupe « un ensemble de disciplines scientifiques dédiées à la description, l'explication, la simulation, des mécanismes de la pensée humaine, animale ou artificielle, et plus généralement de

1. http ://www.syrobo.org

tout système complexe de traitement de l'information capable d'acquérir, conserver, utiliser et transmettre des connaissances »[2]. Depuis mon arrivée au LISSI, mes recherches se sont donc focalisées sur le développement d'un système cognitif artificiel dédié à la robotique développementale.

Après ma thèse de doctorat que j'ai réalisée au Laboratoire Vision Robotique (LVR) de Bourges et qui portait sur le contrôle bio-inspiré d'un robot bipède dans le cadre du projet RABBIT, j'ai intégré le LISSI en septembre 2005. Depuis mon arrivée au sein de ce laboratoire, l'ensemble de mes activités de recherches se sont donc focalisées sur le développement de systèmes cognitifs artificiels appliqués à la robotique et plus particulièrement :

– **La locomotion bipède et l'évitement dynamique d'obstacle** : l'apprentissage de la marche chez l'homme représente un excellent support de travail pour étudier l'acquisition par des systèmes robotisés d'habilités ou compétences nouvelles[3]. Lors de mon arrivée au LISSI, un de mes premiers objectifs a donc été de poursuivre mes travaux initiés lors de ma thèse dans le cadre du projet RABBIT. Les développements réalisés au LISSI depuis 2005 ont porté sur la conception d'une stratégie de contrôle adaptative permettant à un robot bipède, dont les mouvements sont limités au plan sagittal, d'adapter sa marche (longueur de pas, durée du pas, inclinaison du tronc, etc..) automatiquement en fonction des contraintes de l'environnement (irrégularité du sol, obstacle, etc...). La structure algorithmique du système cognitif artificiel dédié au contrôle et à l'acquisition de ces activités motrices est basée sur l'utilisation d'un système d'inférences floues associé à des techniques d'apprentissages par renforcement (Fuzzy-Qlearning) permettant la fusion d'un ensemble de trajectoires de références. Les principaux résultats que nous avons obtenus sont l'adaptation de l'allure de marche en fonction de la modification de l'inclinaison du sol et l'évitement d'obstacle dynamique. Ce travail a aussi été l'occasion de co-encadrer la thèse de Yu Weiwei, thèse réalisée en co-tutelle entre l'Université Paris Est Créteil (UPEC) et Northwestern Polytechnical University (NPU) de Xi'an en chine. Les résultats obtenus dans le cadre de ce travail ont fait l'objet de la publication de 3 articles de revue (ACL-7, ACL-5, ACL-4), 2 chapitres de livre (COS-3, COS-2), 7 articles de conférence (ACTI-19, ACTI-15, ACTI-10, ACTI-8, ACTI-7, ACTI-6, ACTI-5).

– **La perception et l'acquisition autonome de connaissances** : l'autonomie d'un robot repose en partie sur sa capacité à acquérir progressivement des

2. Source Wikipédia
3. Les mots "habilité" et "compétence" sont ici utilisés dans le sens de la traduction du terme anglais "skill"

connaissances nouvelles et savoir les réutiliser dans un contexte différent. Le travail, initié lors de la thèse de Dominik M. RAMIK, nous a permis de proposer une solution basée sur un système cognitif artificiel qui permet à un robot de créer progressivement de nouveaux concepts. Cette thèse apporte des contributions très intéressantes, comme le développement d'un algorithme modélisant les curiosités perceptuelle et épistémique, ainsi que la conception d'un système cognitif haut-niveau permettant, l'acquisition de connaissances à partir d'observations. Les différentes publications associées à ce travail ont fait l'objet de la publication de 3 articles de revues (ACL-10, ACL-9, ACLN-3) et 10 articles de conférences (ACTI-28, ACTI-25, ACTI-24, ACTI-23, ACTI-22, ACTI-21, ACTI-20, ACTI-17, ACTI-14, ACTI-13).

Les systèmes multi-robots et l'intelligence distribuée : une partie de l'intelligence chez l'homme repose sur sa capacité à transmettre et partager ses connaissances, à s'auto-organiser en se répartissant les tâches au sein d'un groupe lors de l'exécution d'un travail commun. La conception de stratégies intelligentes distribuées permettant à un ensemble de robots de collaborer pour réaliser une tâche complexe est donc fondamentale en robotique, mais cela reste un défi scientifique majeur. Les travaux qui ont été effectués dans le cadre de la thèse de Ting WANG ont permis d'aboutir à la proposition d'un système cognitif distribué, où les processus cognitifs sont en partie dissociés et répartis sur des entités matérielles différentes distribuées dans l'espace. Une étude d'application des concepts étudiés a été réalisée, implantée et validée dans le cadre plus particulier de la logistique industrielle. Il est cependant important de noter que l'approche proposée peut se généraliser à des applications très différentes, autre que la logistique. Les résultats obtenus dans le cadre de ce travail ont fait l'objet de la publication de 4 articles de revues (ACL-8, ACL-6, ACLN-2, ACLN-1) et 3 articles de conférences (ACTI-18, ACTI-16, ACTI-12).

A ce jour, l'ensemble de mes recherches a donc fait l'objet de la publication de 17 articles de revues, dont 14 sont indexées par Journal Citation Reports (JCR), 4 chapitres de livres ainsi que de 35 articles de conférences internationales. Ces travaux ont aussi fait l'objet de 4 thèses de doctorat qui ont déjà été soutenues, 3 autres thèses sont en cours. Il est aussi important de noter que les liens tissés entre l'UPEC et Northwestern Polytechnical University lors de la thèse de YU Weiwei ont permis d'initier une collaboration entre le LISSI et différents laboratoires chinois. Cette collaboration a fait l'objet de trois thèses en co-tutelle et d'accueil d'étudiants pour des périodes plus courtes lors de stage de recherche, mais aussi de la soumission de 2 projets ANR "Blancs International II" qui n'ont malheureusement pas abouti. D'autre part, mes activités de recherches, en lien étroit avec certains projets pédagogiques, m'ont permis de financer une plate-forme multi-robots (robots roulants Khepera, robots humanoïdes Nao, logiciels webots, etc.). Cette plate-forme me permet aujourd'hui de valider expérimentalement une grande partie de mes travaux de recherche.

2.2.2 Rayonnement et Responsabilité scientifique

Responsabilité dans des instances nationales

Depuis 2012 : Membre élu permanent de la 61ème section du CNU

Responsabilités dans des instances locales

– Membre élu du comité scientifique de l'IUT de Sénart-Fontainebleau
– Membre élu de conseil de Laboratoire Images, Signaux et Systèmes Intelligents (LISSI)

Comité de sélection recrutement MCF

– Membre des comités de sélection MCF de l'IUT de Cachan en 2011 et 2014

Responsabilités dans des instances locales

– Membre du comité d'organisation de (Industrial External Relations) IJCCI 2011
– Responsable de l'organisation (General Organization Chair) de iCAST 2014

Invitation

– Du 09/06/2012 au 19/06/2012 : Northwestern Polytechnical University, Xi'an, Chine
– Du 30/06/2013 au 10/07/2013 : Northwestern Polytechnical University, Xi'an, Chine
– Du 29/09/2013 au 02/09/2013 : University of Ostrava, Ostarva, République Tchèque
– Du 06/01/2014 au 13/01/2014 : Northwestern Polytechnical University, Xi'an, Chine

Comités de programme de conférences internationales

– Depuis 2007 : Membre du comité de sélection du Workshop Artificial Neural Networks and Intelligent Information Processing (ANNIIP),
– Depuis 2010 : Membre du comité de sélection de International Conférence on Image Processing Theory, Tools and Applications (IPTA),

– Depuis 2010 : Membre du comité de sélection de International Conférence on Neural Computation Theory and Applications» (NCTA)
– Depuis 2013 : Membre du comité de sélection de IEEE International Conférence on Intelligent Data Acquisition and Advanced Computing Systems : Technology and Applications (IDAACS)
– Depuis 2014 : Membre du comité de programme de IEEE International Symposium on Robot and Human Interactive Communication (IEEE RO-MAN)

Expertise

– Depuis 2014 : Expert pour le "Centre de recherche de talents et de promotion d'échanges académiques en technologies avancées de la production aéronautique et aérospatiale" de Northwestern Polytechnical University

2.2.3 Co-encadrement de thèse de doctorat

Boyi ZAHO (Thèse en cours depuis le 01/10/2014)

Titre de la thèse : De la perception distribuée à l'auto-organisation collective des robots dans l'environnement complexe.
Financement : Co-tutelle NPU (Chine)
Date de soutenance prévisionnelle : novembre 2017
Encadrement :
– Kurosh MADANI, Directeur de thèse (50%)
– Christophe SABOURIN, Co-encadrant (50%)

Viachaslau KACHURKA (Thèse en cours depuis le 01/10/2014)

Titre de la thèse : Acquisition et conceptualisation de connaissances en robotique autonome.
Financement : Bourse MESR
Date de soutenance prévisionnelle : novembre 2017
Encadrement :
– Kurosh MADANI, Directeur de thèse (50%)
– Christophe SABOURIN, Co-encadrant (50%)

Hossam FRAIHAT (Thèse en cours depuis le 01/10/2013)

Titre de la thèse : Contribution à la perception distribuée et la construction collective de la connaissance.
Financement : Enseignant second degré.

Date de soutenance prévisionnelle : novembre 2017
Encadrement :
– Kurosh MADANI, Directeur de thèse (50%)
– Christophe SABOURIN, Co-encadrant (50%)

Jingyu WANG (Thèse effectuée d'octobre 2011 à décembre 2014)

Titre de la thèse : Contribution à l'étude et à la mise en œuvre d'un système de perception bio-inspiré basé sur l'attention visuelle et auditive.
Financement : Co-tutelle NPU (Chine)
Date de soutenance : 9 janvier 2014
Durée de la thèse : 38 mois
Encadrement :
– Kurosh MADANI, Directeur de thèse (50%)
– Christophe SABOURIN, Co-encadrant (50%)
Composition du jury :
– Président du jury : Xuelong LI, Professeur, Northwestern Polytechnical University/Chinese Academy of Science (Chine)
– Rapporteur : Lucile ROSSI, Maître de conférences HDR, UMR SPE CNRS - Université de Corse (France)
– Rapporteur : Xinbo GAO, Professeur, Xidian University (Chine)
– Examinateur : Ke ZANG, Professeur, Northwestern Polytechnical University (Chine)
– Examinateur : Christophe SABOURIN, Maître de conférences, Université Paris-Est (France)
– Examinateur : Kurosh MADANI, Professeur, Université Paris-Est (France)
Publications : ACL-13, ACTI-27, ACTI-26

Dominik Maximilián Ramík (Thèse effectuée de octobre 2009 à décembre 2012)

Titre de la thèse : Contribution au traitement d'informations visuelles complexes et à l'extraction autonome des connaissances: application à la robotique autonome.
Financement : Bourse MESR
Date de la soutenance : 10 Décembre 2012
Durée de la thèse : 38 mois
Encadrement :
– Kurosh MADANI, Directeur de thèse (50%)
– Christophe SABOURIN, Co-encadrant (50%)
Composition du jury :
– Président du jury : Patrick GARDA Professeur, Université Pierre et Marie Curie
– Rapporteur : Serge MIGUET, Professeur, Université Lyon 2
– Rapporteur : Samia BOUCHAFA, Professeur, Université Evry-Val d'Essonne
– Examinateur : Eva VOLNA, Professeur, University of Ostrava
– Examinateur : Christophe SABOURIN, Maître de conférences, Université Paris-Est

- Examinateur : Kurosh MADANI, Professeur, Université Paris-Est

Publications : ACL-10, ACL-9, ACL-6, ACLN-3, ACTI-28, ACTI-25, ACTI-24, ACTI-23, ACTI-22, ACTI-20, ACTI-17, ACTI-14, ACTI-13
Situation actuelle : Enseignant

Ting Wang (Thèse effectuée de octobre 2008 à juillet 2012)

Titre de la thèse : Contribution à l'étude, à la conception et à la mise en œuvre de stratégie de contrôle intelligent distribué en robotique collective.
Financement : Bourse gouvernement chinois
Date de la soutenance : 11 Juillet 2012
Durée de la Thèse : 45 mois
Encadrement :

- Kurosh MADANI, Directeur de thèse (50%)
- Christophe SABOURIN, Co-encadrant (50%)

Composition du jury :

- Président du jury : Gilles BERNARD, Professeur, Université PARIS 8
- Rapporteurs : Hichem MAAREF, Professeur, Université Evry-Val d'Essonne
- Rapporteur : Vladimir GOLOVKO, Professeur, Brest State Technical University
- Examinateur : Yacine AMIRAT, Professeur, Université Paris-Est
- Examinateur : Christophe SABOURIN, Maître de conférences, Université Paris-Est
- Examinateur : Kurosh MADANI, Professeur, Université Paris-Est

Publications : ACL-8, ACL-6, ACLN-2, ACLN-1, ACTI-18, ACTI-16, ACTI-12
Situation actuelle : Chercheur - Nanjing University (Chine)

Yu Weiwei (Thèse effectuée de octobre 2007 à février 2011)

Titre de la thèse : Contribution à l'étude et à la mise en œuvre de stratégies adaptatives de commandes intelligentes : application au contrôle de systèmes dynamiques complexes.
Financement : Co-tutelle NWPU (Chine)
Date de soutenance : 23 février 2011
Durée de Thèse : 41 mois
Encadrement :

- Kurosh MADANI, Directeur de thèse (50%)
- Christophe SABOURIN, Co-encadrant (50%)

Composition du jury :

- Président du jury : Xiansheng QIN, Professeur, Northwestern Polytechnical University (Chine)
- Rapporteurs : Yuanying QIU, Professeur, Xidian University (Chine)

– Rapporteur : Tianshi LI, Professeur, Xi'an Jiaotong University (Chine)
– Examinateur : Jie YAN, Professeur,Northwestern Polytechnical University (Chine)
– Examinateur : Christophe SABOURIN, Maître de conférences, Université Paris-Est (France)
– Examinateur : Kurosh MADANI, Professeur, Université Paris-Est (France)

Publications : ACL-7, COS-3, ACTI-19, ACTI-15, ACTI-10, ACTI-9, ACTI-8, ACTI-7
Situation actuelle : Lecturer NWPU (Xián, Chine)

2.2.4 Encadrement de stage

Dayana HASSAN (Stage M2 effectué de Mars à Septembre 2015)

– Diplôme préparé : Master 2 Systèmes complexes, Technologies de l'Information – (UPEC)
– Durée du stage : 5 mois
– Sujet de stage : Extraction de caractéristiques spatiales de l'environnement à partir d'une perception pseudo-3D

Sen WANG (Stage doctoral effectué de Mai à Octobre 2013)

– Diplôme préparé : Phd Northwestern Polytechnical University, Xi'an, Chine
– Durée du stage : 6 mois
– Sujet de stage : Theoretical study and application on transfer learning across heterogeneous robots

Viachaslau A. Kachurka (Stage M2 effectué de Septembre à Octobre 2013)

– Diplôme préparé : Master Brest State Technical University
– Durée du stage : 2 mois
– Sujet de stage : A Statistical Approach to Human-Like Visual Attention : Application to Woodland Fires' Detection

Assia AZIEZ(Stage M2 effectué de Mars à Septembre 2012)

– Diplôme préparé : Master 2 Systèmes complexes, Technologies de l'Information – (UPEC)
– Durée du stage : 5 mois
– Sujet de stage : Autonomie ajustable en robotique, modélisation par réseaux de pétri flous surveillés

Ouerdia MEGHERBI(Stage M2 effectué de Mars à Septembre 2012)

- Diplôme préparé : Master 2 Systèmes complexes, Technologies de l'Information – (UPEC)
- Durée du stage : 5 mois
- Sujet de stage : Perception et représentation sémantique de l'environnement

Trong-Duc PHUNG (Stage DUT GEII effectué du 12 Mai au 18 juillet 2013)

- Diplôme préparé : DUT Génie Électrique et Informatique Industrielle (IUT de Sénart Fontainebleau)
- Durée du stage : 2 mois
- Sujet de stage : Contrôle d'un robot Nao par joystick.

Mélanie COUDRAY (Stage DUT GEII effectué du 15 avril au 21 juin 2013)

- Diplôme préparé : DUT Génie Électrique et Informatique Industrielle (IUT de Sénart Fontainebleau)
- Durée du stage : 2 mois
- Sujet de stage : Mise en œuvre d'un robot Wifibot.

Fabien GAUTERO (Stage DUT GEII effectué du 12 avril au 9 juillet 2010)

- Diplôme préparé : DUT Génie Électrique et Informatique Industrielle (IUT de Sénart Fontainebleau)
- Durée du stage : 2 mois
- Sujet de stage : Étude, conception et mise en œuvre de stratégies de contrôles intelligents distribués en robotique collective.

Kathleen TRIVAL (Stage DUT GEII effectué du 27 avril au 3 juillet 2009)

- Diplôme préparé : DUT Génie Électrique et Informatique Industrielle (IUT de Sénart Fontainebleau)
- Durée du stage : 2 mois
- Sujet de stage : Mise en œuvre d'un robot humanoïde NAO.

Yann ROSSIGNOL (Stage DUT GEII effectué du 10 avril 2007 au 15 juin 2007)

- Diplôme préparé : DUT Mesures Physiques option Techniques Instrumentales (IUT de Bourges)

- Durée du stage : 2 mois
- Sujet de stage : Mise en place d'une plate-forme expérimentale multi-robots à base de plusieurs robots de type Khepera III.

Chapitre 3

Liste des Publications

3.1 Articles dans des revues internationales répertoriées dans JCR

ACL-14 YU W., Feng H., Feng Y., Madani K. and Sabourin C. Nonholonomic mobile system control by combining EEG-based BCI with ANFIS. Bio-Medical Materials and Engineering, Vol. 26, pages : 1125-1133, **2015**. IOS Press, ISSN : 0959-2989, $\mathrm{IF}_{2015} = 1.091$.

ACL-13 Wang J., Zhang K., Madani K. and Sabourin C. Salient environmental sound detection framework for machine awareness. Neurocomputing, Vol. 152, pages : 444–454, **2015**. Elsevier, ISSN : 0925-2312, $\mathrm{IF}_{2014} = 2.083$.

ACL-12 Ramik D.M., Madani K. and Sabourin C. A Soft-Computing basis for robots' cognitive autonomous learning. Soft Computing, Vol. 19(9), pages : 2407-2421, **2014**. Springer Berlin Heidelberg, ISSN : 1432-7643, $\mathrm{IF}_{2014} = 1,271$.

ACL-11 Ramik D.M., Sabourin C., Moreno R. and Madani K. A Machine learning based intelligent vision system for autonomous object detection and recognition. Applied Intelligence, Vol 40(2), pages : 358-375, **2014**. Springer, ISSN : 0924-669X, $\mathrm{IF}_{2014} = 1,853$.

ACL-10 Ramik D.M., Sabourin C. and Madani K. Autonomous knowledge acquisition based on artificial curiosity: Application to mobile robots in indoor environment. Robotics and Autonomous Systems, Vol 61(12), pages : 1680-1695, **2013**. Elsevier, ISSN : 0921-8890, $\mathrm{IF}_{2014} = 1.256$.

ACL-9 Ramik D.M., Madani K. and Sabourin C. From visual patterns to semantic description: A cognitive approach using artificial curiosity as the foundation. Pattern Recognition Letters, Vol 34(14), pages : 1577-1588, **2013**. Elsevier, ISSN : 0167-8655, $IF_{2014} = 1.551$.

ACL-8 Wang T., Sabourin C. and Madani K. A novel path planning approach for multi-robot based transportation. International Journal of Robotics and Automation, Vol 28(3), pages : 218-225, **2013**. ACTA Press, ISSN : 0826-8185, $IF_{2014} = 0.658$.

ACL-7 Sabourin C., Yu W. and Madani K. Gait pattern based on CMAC neural network for robotic applications. Neural Processing Letters, Vol 38(2), pages : 261-279, **2013**. Springer, ISSN : 1370-4621, $IF_{2014} = 1.448$.

ACL-6 Wang T., Ramik D.M., Sabourin C. and Madani K. Intelligent systems for industrial robotics: application in logistic field. Industrial Robot : An International Journal, Vol. 39(3), pages : 251-259, **2012**. Emerald Group Publishing Limited, ISSN : 0143-991X, $IF_{2014} = 0.635$.

ACL-5 Madani K. and Sabourin C. Multi-level cognitive machine-learning based concept for human-like "artificial" walking: Application to autonomous stroll of humanoid robots. Neurocomputing, Vol. 74(8), pages : 1213-1228, **2011**. Elsevier, ISSN : 0925-2312, $IF_{2014} = 2.083$.

ACL-4 Sabourin C., Madani K. and Bruneau O. Autonomous biped gait pattern based on Fuzzy-CMAC neural networks. Integrated Computer-Aided Engineering. Vol. 14(2), pages : 173-186, **2007**. IOS Press, ISSN :1069-2509, $IF_{2014} = 4.667$.

ACL-3 Sabourin C., Bruneau O. and Buche G. Control strategy for the robust dynamic walk of a biped robot. The International Journal of Robotics Research, Vol 25(9), pages : 843-860, **2006** . SAGE Publications, ISSN :0278-3649, $IF_{2014} = 2.540$.

ACL-2 Sabourin C. and Bruneau O. Robustness of the dynamic walk of a biped robot subjected to disturbing external forces by using CMAC neural networks. Robotics and Autonomous Systems. Vol. 51(2), pages : 81-99, **2005**. Elsevier, ISSN :0921-8890, $IF_{2014} = 1.256$.

ACL-1 Sabourin C., Bruneau O. and Fontaine J.G. Start, stop and transition of velocities on an underactuated bipedal robot without reference trajectories. Internationnal Journal of Humanoid Robotics. Vol. 1(2), pages : 349-374, **2005**. World Scientific, ISSN : 0219-8436, $IF_{2014} = 0.408$.

3.2 Articles dans des revues internationales non répertoriées dans JCR

ACLN-3 Madani K., Ramik D.M. and Sabourin C. Multilevel cognitive machine-learning-based concept for artificial awareness: application to humanoid robot awareness using visual saliency. Applied Computational Intelligence and Soft Computing, Vol. 2012, pages : 1-11, **2012**. Hindawi Publishing co, ISSN : 1687-9724.

ACLN-2 Wang T., Sabourin C. and Madani K. ANFIS controller for nonholonomic robots. Majlesi Journal of Electrical Engineering. Vol. 5(2), pages : 31-37, **2011**. ISSN : 2345-377X.

ACLN-1 Wang T., Gautero F., Sabourin C. and Madani K. A neural fuzzy inference based adaptive controller for nonholonomic robots, COMPUTING, Special Issue on Neural Networks and Artificial Intelligence, Vol. 10(1), pages : 56-65, **2011**. ISSN : 1727-6209.

3.3 Chapitres de livres

COS-4 Madani K., Ramik D. M. and Sabourin C. Autonomous Knowledge Discovery Based on Artificial Curiosity-Driven Learning by Interaction. Chapter 4 of Advances in Intelligent Robotics and Collaborative Automation, pages : 73-94, **2015**, R. Duro, & Y. Kondratenko (Ed.), ISBN 9788793237032, River Publishers, Denmark.

COS-3 Yu W., Madani K. and Sabourin C. CMAC structure optimization based on modified Q-learning approach and its applications, Computational Intelligence, Studies in Computational Intelligence, Vol. 465, pages : 347-359, **2013**. Springer, ISBN : 978-3-642-35637-7.

COS-2 Sabourin C., Madani K. and Bruneau O. (**2008**). Autonomous gait pattern for a dynamic biped walking. In Informatics in Control Automation and Robotics (Selected Papers from the International Conference on Informatics in Control Automation and Robotics 2006), Vol. 15, pages : 123-139. Springer, ISBN : 978-3-540-79141-6.

COS-1 Sabourin C., Madani K. and Bruneau O. Towards adaptive control strategy for biped robots. Humanoid Robots : Human-like Machines, pages : 191-120, **2007**. Itech, Vienna, Austria, ISBN : 978-3-902613-07-3.

3.4 Conférences internationales

ACTI-35 Hassan D., Madani K. and Sabourin C. Dual 2-D Images-Based Approach for Objects' 3-D Characterization and Localization for Machine-Awareness in Indoor Environment. IEEE 7th International Joint Conference on Awareness Science and Technology (**iCAST 2015**), pages : 1-6, IEEE. Qinghuangdao, China, September 22-24, 2015.

ACTI-34 Kachurka V., Madani K., Sabourin C and Golovko V. Visual Saliency and Visual Attention in Computer Vision for Real-World Applications. 8th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems (**IDAACS 2015**), pages : 1-6, IEEE. Warsaw, Poland, September 24 – 26, 2015.

ACTI-33 Fraihat H., Madani K. and Sabourin C. Soft-Computing Based Fast Visual Objects' Distance Evaluation for Robots' Vision. 8th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems (**IDAACS 2015**), pages : 1-6, IEEE. Warsaw, Poland, September 24 – 26, 2015.

ACTI-32 Wang J., Zhang K., Madani K., Sabourin C. and Zhang J. Salient Foreground Object Detection based on Sparse Reconstruction for Artificial Awareness. 12th International Conference on Informatics in Control, Automation and Robotics **IEEE/ICINCO 2015**, pages : 430 – 437, SCITEPRESS Digital Library. Colmar, France, July 21 – 23, 2015.

ACTI-31 Kachurka V., Madani K., Sabourin C and Golovko V. From Human Eye Fixation to Human-likeAutonomous Artificial Vision. 13th International Work-Conference on Artificial Neural Networks (**IWANN 2015**), pages : 171-184, Springer International Publishing, ISBN : 978-3-319-19257-4,

ACTI-30 Wang J., Zhang K., Madani K. and Sabourin C. Multi-scale feature based salient environmental sound recognition for machine awareness. IEEE 6th International Joint Conference on Awareness Science and Technology (**iCAST 2014**), pages : 1-6, IEEE. Paris, France, October, 2014.

ACTI-29 Kachurka V., Madani K., Sabourin C and Golovko V. A statistical approach to human-like visual attention and saliency detection for robot vision: application to wildland fires' detection. 8th International Conference on Neural Networks and Artificial Intelligence (**ICNNAI 2014**), vol. 440, pages : 124-135, Springer International Publishing, ISBN : 978-3-319-08200-4. Brest, Belarus, June, 2014.

ACTI-28 Ramik D.M., Madani K and Sabourin C. At odds with curious cats, curious robots acquire human-like intelligence. 8th International Conference on Neural Networks and Artificial Intelligence (**ICNNAI 2014**), vol. 440, pages : 122-123, Springer International Publishing, ISBN : 978-3-319-08200-4. Brest, Belarus, June, 2014.

ACTI-27 Wang J., Zhang K., Madani K. and Sabourin C. Heterogeneous information saliency features' fusion approach for machine's environment sounds based awareness. International Joint Conference on Awareness Science and Technology and Ubi-Media Computing (**iCAST-UMEDIA**), pages : 197-205. Aizu, Japan, Nov. 2013.

ACTI-26 Wang J., Zhang K., Madani K. and Sabourin C. A visualized acoustic saliency feature extraction method for environment sound signal processing. TENCON 2013 IEEE Region 10 Conference (31194) , pages : 1-4, ISSN : 2159-3442. Xi'an, China, Oct. 2013.

ACTI-25 Ramik D.M., Sabourin C. and Madani K. Artificial curiosity driven autonomous knowledge discovery based on learning by interaction. 7th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems (**IDAACS 2013**), pages : 855-860, ISBN : 978-1-4799-1426-5. Berlin, Germany, Sep. 2013.

ACTI-24 Ramik D.M., Madani K and Sabourin C. Artificial curiosity emerging human-like behaviour - A fundation for fully autonomous cognitive machines. International Conference on Neural Computation Theory and Applications (**NCTA 2013**), pages : 407 - 419, SCITEPRESS Digital Library. Vilamoura, Algarve, Portugal, Sep. 2013.

ACTI-23 Ramik D.M., Madani K and Sabourin C. A cognitive approach for robots' autonomous learning. 12th International Work-Conference on Artificial Neural Networks (**IWANN 2013**), pages : 309-320, Springer Berlin Heidelberg, ISBN : 978-3-642-38678-7. Puerto de la Cruz, Tenerife, Spain, June 2013.

ACTI-22 Ramik D.M., Sabourin C. and Madani K. Autonomous knowledge acquisition based on active learning: application to humanoid robots in indoor environment. IEEE International Conference on Robotics and Automation (**ICRA 2013**), pages : 1779-1784, ISSN : 1050-4729. Karlsruhe, Allemagne, May 2013.

ACTI-21 Amarger V., Ramik D., Sabourin C., Madani K., Moreno R., Rossi L. and Graña M. Spherical coordinates framed RGB color space dichromatic reflection model based image segmentation: application to wildland fire's outlines extraction. International Conference on Image Processing Theory, Tools and Applications (**IPTA 2012**), pages : 19-24, ISSN : 2154-5111 Istanbul, Turkey, Oct. 2012.

ACTI-20 Ramik D., Sabourin C. and Madani K. "Hybrid salient object extraction approach with automatic estimation of visual attention scale". 7th International Conference In Signal-Image Technology and Internet-Based Systems (**SITIS 2011**), pages : 438-445, ISSN :2154-5111, Dijon, France, Nov. 2011

ACTI-19 Yu W., Madani K. and Sabourin C. CMAC structure optimization based on modified Q-learning approach and its applications. International Conference on Neural Computation Theory and Applications (**NCTA 2011**), pages. 283 - 288, SCITEPRESS Digital Library. Paris, France, Oct 2011.

ACTI-18 Wang T., Sabourin C. and Madani K. Strategy based on machine learning for the control of a rigid formation in a multi-robots frame. 8th International Conference on Informatics in Control, Automation and Robotics **ICINCO 2011**, pages : 300 - 303, SCITEPRESS Digital Library. Noordwijkerhout, The Netherlands, Jul, 2011.

ACTI-17 Ramík D., Sabourin C. and Madani K. , A Cognitive Approach for Robots' Vision Using Unsupervised Learning and Visual Saliency. 11th International Work-Conference on Artificial Neural Networks (**IWANN 2011**), LNCS series, vol. 6691, pages : 81-88, Springer Berlin Heidelberg, ISBN : 978-3-642-21501-8. Torremolinos-Málaga, Spain, June, 2011.

ACTI-16 Wang T., Gautero F., Sabourin C. and Madani K. A Neural Fuzzy Inference Based Adaptive Controller Using Learning Process for Nonholonomic Robots. 11th International Work-Conference on Artificial Neural Networks (**IWANN 2011**), LNCS series, Vol. 6691, pages : 65-72, Springer Berlin Heidelberg, ISBN 978-3-642-21501-8. Torremolinos-Málaga, Spain, June, 2011.

ACTI-15 Yu W., Madani K. and Sabourin C. Self-optimizing for the Structure of CMAC neural network. 3rd IEEE International Symposium on Knowledge Acquisition and Modeling (**KAM 2010**), pages : 432-436, ISBN : 978-1-4244-8004-3. Wuhan, China, Oct, 2010

ACTI-14 Ramik D.M., Sabourin C. and Madani K. Towards Human Inspired Semantic Slam. 7th International Conference on Informatics in Control Automation and Robotics (**ICINCO 2010**), pages : 360-363. SCITEPRESS Digital Library. Funchal, Madeira, Portugal, June, 2010

ACTI-13 Ramik D.M., Sabourin C. and Madani K. On Human Inspired Semantic SLAM's Feasibility. 6th International Workshop on Artificial Neural Networks and Intelligent Information Processing (**Workshop ANNIIP 2010**), pages : 99-108, SCITEPRESS Digital Library. Funchal, Madeira, Portugal, June, 2010

ACTI-12 Wang T., Sabourin C. and Madani K. ANFIS controller for nonholonomic robots. 5th International Conference on Neural Networks and Artificial Intelligence (**ICNNAI 2010**), In Proceedings pages : 320-325. Brest, Belaruss, June, 2010.

ACTI-11 Madani K., Amarger V. and Sabourin C. ANN Based Solutions: It Is Time to Defeat Real-World and Industrial Dilemmas. 10th International Work-Conference on Artificial Neural Networks (**IWANN 2009**), Vol. 5517, pages : 1328-1335, ISBN 978-3-642-02477-1, Springer Berlin Heidelberg. Salamanca, Spain, June, 2009.

ACTI-10 Yu W., Sabourin C. and Madani K., Design of Footstep Planning Controller for Humanoid Robot in Dynamic Environment. IEEE International Symposium on Knowledge Acquisition and Modeling Workshop (**KAM 2008**). In Proceedings pages : 840-843, ISBN : 978-1-4244-3530-2. Wuhan, China, Dec. 2008.

ACTI-9 Sabourin C., Madani K., Yu W. and Yan J. Obstacle avoidance strategy for biped robot based on fuzzy Q-learning, Eleventh International conference on climbing and walking robots and the support technologies for mobile machines (**CLAWAR 2008**), In Proceedings pages : 695-702, ISBN : 978-981-283-576-5. Coimbra, Portugal, Sept. 2008.

ACTI-8 Sabourin C., Madani K., Yu W. and Yan J. Footstep Planning For Biped Robot Based On Fuzzy Q-Learning Approach. 5th International Conference on Informatics in Control, Automation and Robotics (**ICINCO 2008**), In Proceedings pages : 183 - 188, SCITEPRESS Digital Library. Madeira, Portugal, May 2008.

ACTI-7 Yu W., Sabourin C., Madani K. and YAN J. CMAC Neural network's Structure Optimization for Function Approximation. 3rd International Conference on Neural Networks and Artificial Intelligence (**ICNNAI 2008**), In Proceedings pages : 320-325. Minsk, Belaruss, May, 2008.

ACTI-6 Sabourin C., Madani K. and Bruneau O. Autonomous Gait Pattern For A Dynamic Biped Walking. 3rd International Conference on Informatics in Control, Automation and Robotics (**ICINCO 2006**), In Proceedings pages : 26-33, SCITEPRESS Digital Library. Setual, Portugal, Aug. 2006.

ACTI-5 Sabourin C., Madani K. and Bruneau O. A Fuzzy-CMAC Based Hybrid Intuitive Approach for Biped Robot's Adaptive Dynamic Walking. International Conference on Neural Networks and Artificial Intelligence (**ICNNAI 2006**). In Proceedings pages : 78-83. Brest, Belarus, June 2006.

ACTI-4 Sabourin C., Bruneau O. and Buche G. Experimental validation of a robust control strategy for the robot rabbit, IEEE International Conference on Robotics and Automation (**ICRA 2005**). In Proceedings pages : 2393-2398, ISBN : 0-7803-8914-X . Barcelona, Spain, April 2005.

ACTI-3 Sabourin C, Bruneau O and Fontaine J. Learning of the Dynamic Walk of an Under-Actuated Bipedal Robot: Improvement of the Robustness by Using CMAC Neural Networks. 7th International Conference of Climbing and Walking Robots (**CLAWAR 2004**). In Proceedings pages : 543-550. Springer Berlin Heidelberg. ISBN 978-3-540-22992-6. Madrid, Spain, Sep. 2004.

ACTI-2 Sabourin C., Bruneau O. and Fontaine J. Pragmatic rules for real-time control of the dynamic walking of an under-actuated biped robot, IEEE International Conference on Robotics and Automation (**ICRA 2004**). In Proceedings pages : 4216-4221, ISSN :1050-4729. New Orleans, LA, USA. April 2004,

ACTI-1 Sabourin C., Bruneau O. and Fontaine J. Intuitive And Fuzzy Control of an underactuated biped robot without reference trajectories. 11th World Congress in Mechanism and Machine Science (**IFToMM**), In Proceedings Vol 1-5, pages : 1736-1740. Tianjin, China, April 2004.

3.5 Communications orales - Congrès nationaux

COM-6 Sabourin C. and Madani K. Perception, langage, curiosité : éléments clés pour la conceptualisation de connaissances en robotique interactive. Worshop Affects Compagnons Artifciels, Interaction (WACAI 2014) Rouen, 30 Juin et 1er Juillet 2014

COM-5 Sabourin C. and Madani K. Interaction homme-robot et conceptualisation de connaissances. Journées Nationales de la Robotique Interactive. Cité de l'espace, Toulouse, 27 et 28 novembre 2014

COM-4 Sabourin C. and Madani K. Interaction homme-robot et conceptualisation de connaissances. Journées Nationales de la Robotique Interactive. Cité de l'espace, Toulouse, 27 et 28 novembre 2014

COM-3 Ramik D.M., Sabourin C. and Madani K. A Real-time Approach to Humanoid Robot Learning of Objects through Visual Saliency. Journées Nationales de la Robotique Humanoïde, Toukouse, 31 mars au 1 avril, 2011.

COM-2 Ramik D.M., Sabourin C. and Madani K. Designing Human Inspired SLAM for Humanoid Robots. Journées Nationales de la Robotique Humanoïde, Futuroscope, Poitiers, 3 et 4 Juin 2010.

COM-1 Sabourin C. and Madani K. Stratégie d'évitement d'obstacles dynamiques pour robots bipèdes. Journées Nationales de la Robotique Humanoïde, Paris, 13 et 14 Mai 2008.

II - Partie Scientifique

Introduction

Depuis le début du $20^{ème}$ siècle, robotique et intelligence artificielle ont toujours suscité dans l'imaginaire des hommes des peurs, des angoisses ou bien des rêves les plus fous. Amis pour les uns, ennemis pour les autres, les robots doués d'une certaine « intelligence » n'ont pas cessé d'alimenter la littérature de science fiction. Comme précurseur, on peut citer Karel Capek qui est l'auteur de la pièce de théâtre RUR en 1920, ou bien Isaac Asimov pour ses romans de science fiction et les fameuses trois lois de la robotique censées gérer le comportement des robots. Cependant, si le siècle dernier a vu l'essor de la robotique industrielle, force est de reconnaître que les robots sont encore loin d'égaler les performances humaines, notamment du point de vue de l'intelligence. En effet, aujourd'hui, nous savons parfaitement contrôler des robots pour la réalisation de tâches répétitives planifiées à l'avance comme c'est le cas dans l'industrie. Nous savons aussi concevoir des systèmes semi-autonomes comme par exemple dans le cas des robots destinés à l'exploration spatiale. Et très prochainement nous aurons à notre disposition des véhicules personnels, en partie ou complètement autonomes, pour nous transporter sur de longues distances en toute sécurité. Cependant, la conception de systèmes autonomes ne pourra suffire pour dépasser les enjeux scientifiques et technologiques de la robotique du $21^{ème}$ siècle qui portera sur le service et l'assistance à la personne. Car si les performances des stratégies de contrôles utilisées en robotique sont incontestables, notamment dans le domaine de la robotique industrielle, il n'en est pas de même lorsque les robots évoluent dans des environnements dynamiques en contact permanent avec l'homme. Or le développement économique de la robotique de service et d'assistance à la personne, sera intimement liée à la capacité des robots à s'intégrer naturellement dans leur environnement, pour cohabiter avec des êtres humains.

D'un point de vue scientifique, les problèmes majeurs de la robotique de service et d'assistance à la personne ne viendront pas particulièrement des tâches que les robots devront effectuer, mais plutôt du contexte, difficilement prévisible, dans le lequel ils devront le faire. Ces systèmes robotisés devront donc faire preuve d'une très grande souplesse d'adaptation en développant, au fil de leurs expériences, de nouvelles capacités cognitives leur permettant ainsi d'apprendre à cohabiter progressivement avec les êtres humains. C'est pour ces raisons que depuis de nombreuses années, des scientifiques tentent de concevoir des robots dotés de capacités cognitives similaires à un être humain. L'être humain est donc une source d'inspiration privilégiée, pas seulement d'un point de vue morphologique mais aussi d'un point de vue fonctionnel, pour créer des entités robotiques intelligentes. Dans ce contexte, les sciences cognitives, qui prennent en partie leurs sources dans les fondements de la cybernétique, offrent un espace de travail très intéressant pour la conception de robots capables d'acquérir et d'utiliser progressivement des connaissances et des compétences nouvelles.

Les sciences cognitives concernent l'étude des capacités et processus mentaux qui, au moyen d'un traitement de l'information, engendrent, transmettent, modifient, utilisent, conservent de la connaissance. Les sciences cognitives, ou sciences de la cognition, ont donc pour but de décrire, de comprendre, de modéliser et de simuler les principales fonctions de l'esprit comme le langage, le raisonnement, la perception, la coordination motrice, etc... [Andler 04]. C'est à la fin des années 50 qu'ont émergé les sciences cognitives notamment avec la théorie du cognitivisme, mais c'est seulement dans les années 70 que le terme « sciences cognitives » est apparu. Aujourd'hui, les sciences cognitives couvrent plusieurs domaines scientifiques qui sont les sciences de l'homme et de la société (sciences sociales, linguistique, philosophie), les sciences de la vie (psychologie, neuroscience) ainsi que les sciences et techniques de l'information et de la communication (intelligence artificielle, informatique). Au sein des sciences cognitives, deux grands mouvements se sont opposés : le cognitivisme et le connexionnisme. Pour le cognitivisme, le cerveau convertit la perception du monde extérieur en représentations symboliques internes qu'il manipule ensuite à l'aide d'un ensemble de règles prédéfinies pour calculer les sorties. On peut donc comparer le cerveau à un ordinateur qui traite l'information via des processus purement symboliques. Pour les adeptes du cognitivisme comme Jerry Fodor, il est possible de dissocier la partie traitement des supports matériels. Le « corps » a donc une importance marginale puisque un ordinateur est capable de simuler complètement le comportement d'un cerveau. Dans le cognitivisme, « l'esprit » est divisé en modules spécifiques. Par exemple, il existe un module pour la perception, un autre pour le langage, etc.. Le cognitivisme a été largement prédominant dans les sciences cognitives des années 1950 aux années 1980. Puis au début des années 80, le connexionnisme a remis en question le cognitivisme. En effet, si généralement, l'approche cognitiviste permet de modéliser un raisonnement, il lui est plus difficile de solutionner des tâches liées à la perception ou au contrôle sensori-moteur. Le connexionnisme, quant à lui, propose de modéliser le fonctionnement du cerveau (l'esprit) à l'aide de réseaux interconnectés (réseaux de neurones). Le fonctionnement en parallèle de ces réseaux doit permettre, à partir de stimuli d'entrées, de reproduire des activités cognitives comme la perception, le langage, le contrôle sensori-moteur, etc.. Quoi qu'il en soit, les deux approches semblent complémentaires et le plus important aujourd'hui est peut être de savoir si la cognition peut être complètement « désincarnée » ou bien au contraire nécessairement « incarnée ». En effet, de nombreux chercheurs en sciences cognitives considèrent que la cognition ne peut résulter que d'une suite d'interactions entre un système nerveux, incarné dans un organisme corporel, et son environnement. Ceci a notamment conduit Francisco Varela [Varela 99] à proposer la théorie de l'« énaction » qui met l'accent sur la manière dont les organismes et les esprits humains s'organisent eux-mêmes en interaction avec l'environnement. Pour Francisco Varela, la cognition est le résultat d'une succession d'expériences sensori-motrices et la connaissance découle d'une interprétation de notre perception du monde.

Les systèmes cognitifs artificiels destinés à simuler le comportement de l'esprit humain, qui s'inspirent directement des différents paradigmes des sciences cognitives, peuvent être classés en deux grandes catégories : les approches cognitivistes utilisant une représentation symbolique des informations et les approches basées sur le connexionnisme et l'émergence de systèmes [Vernon 07]. Certaines de ces approches ont été utilisées en robotique comme par exemples [Benjamin 04] [Laird 12] [Burghart 05]. Cependant, la robotique développementale qui repose sur le paradigme de l'énaction [Vernon 10] semble être l'axe de recherche le plus prometteur car le savoir et le savoir-faire d'un robot dépend en grande partie de ses propres expériences. En effet, le paradigme de l'énaction repose sur l'idée qu'un système cognitif développe sa propre compréhension du monde par l'intermédiaire de ses interactions avec son environnement. Ceci implique aussi que le système cognitif fonctionne de manière autonome et qu'il génère ses propres modèles afin d'interpréter sa perception du monde dans lequel il évolue. L'énaction fournit aussi un cadre théorique permettant de classer et de différencier les aptitudes phylogéniques, spécifique à une classe de systèmes biologiques ou artificiels, des aptitudes ontogéniques qui contribuent au développement et à l'identité de chaque système.

Le fil conducteur des recherches présentées dans ce mémoire s'appuie sur le principe de la robotique développementale et plus particulièrement sur le paradigme de l'énaction. L'idée n'est donc pas de développer un robot intelligent, mais plutôt de concevoir un robot qui soit capable de le devenir. En comparaison des travaux présentés par David Vernon dans [Vernon 11], l'originalité du travail présenté dans ce mémoire repose sur le fait que nous avons proposé de décomposer le Système Cognitif Artificiel (SCA) en deux parties distinctes : la première regroupe des Processus Cognitifs que nous qualifierons d'« Inconscients » (PCI) et la deuxième

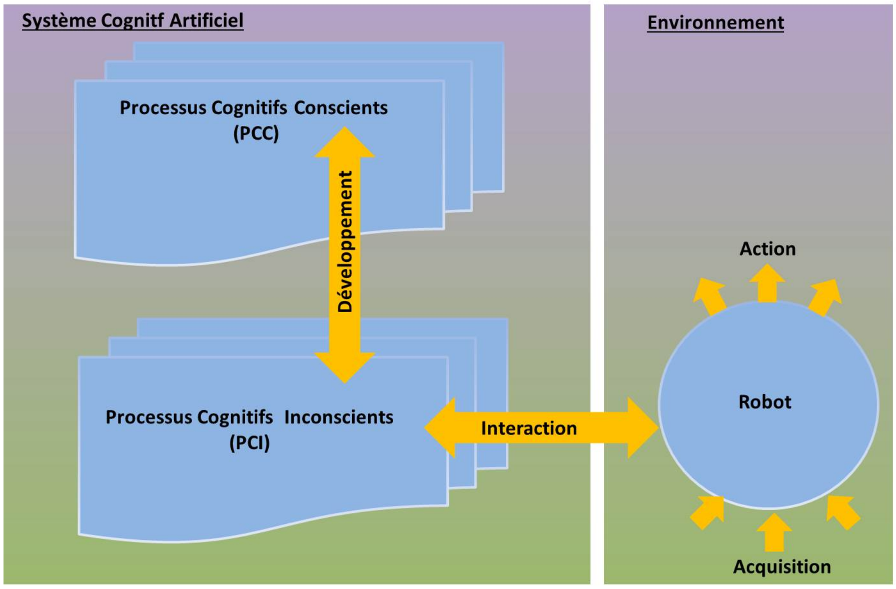

FIGURE 3.5.1: Schématisation du Système Cognitif Artificiel (SCA) : Les Processus Cognitifs Inconscients (PCI) correspondent aux aptitudes pré-programmées ou apprises alors que les Processus Cognitifs Conscients (PCC) contribuent au développement de nouvelles aptitudes.

concerne les Processus Cognitifs « Conscients » (PCC). Le terme « inconscient » signifie ici que les PCI s'exécutent de manière quasi-automatique alors le terme « conscient » implique que les PCC s'exécutent de manière volontaire. Ce système cognitif, qui est illustré par la figure 3.5.1, perçoit et agit sur son environnement via les capteurs et les effecteurs de la structure robotique. Les processus cognitifs inconscients correspondent aux aptitudes pré-programmées ou apprises fonctionnant de manière quasi-automatique, alors que les processus cognitifs conscients contribuent au développement, à l'apprentissage, de nouvelles aptitudes. La cognition associée au robot est donc le résultat d'un processus de développement par lequel le robot devient progressivement plus habile et acquiert les connaissances lui permettant d'interpréter le monde qui l'entoure. Ce mémoire n'a pas pour ambition de définir une architecture cognitive complète permettant à un robot de devenir « intelligent », mais il a pour but de donner des exemples de mise en œuvre concrète du système cognitif artificiel tel qu'il est représenté sur la figure 3.5.1.

Le chapitre 4 sera consacrée au contrôle moteur et l'acquisition d'aptitude motrices complexes et plus particulièrement la locomotion bipède. En effet, bien qu'il soit facile pour un être humain de marcher, de courir, d'éviter ou d'enjamber des obstacles, il n'en est pas de même pour un robot humanoïde. Même si certaines études très récentes ont montré des avancés importantes dans ce domaine, notamment par les travaux menés par Boston Dynamics [1], les structures poly-articulées bipèdes restent des systèmes très complexes à contrôler car cela nécessite la prise en compte de nombreuses contraintes (unilatéralité du contact, grand nombre de degrés de liberté, couplage non linéaire, puissance des actionneurs, etc..). Par conséquent, un des enjeux de la conception de robots humanoïdes performants reste encore de nos jours le contrôle de la locomotion au sens large, c'est-à-dire donner à de tels robots les capacités de marcher à différentes allures tout en s'adaptant à la nature et au relief du terrain, de courir, de franchir ou d'éviter des obstacles, ainsi que de planifier des chemins dans un environnement dynamique. Les résultats des travaux présentés dans ce chapitre s'inscrivent dans la continuité de ma thèse de doctorat qui portait sur le contrôle d'un robot bipède sans pied : le robot RABBIT. Bien que ces travaux se soient focalisés sur la locomotion, la structure de système cognitif artificiel peut servir de base pour la conception d'un système nerveux artificiel dédié au contrôle et l'acquisition d'activités motrices.

Le chapitre 5 sera quant à lui consacré à la perception et la conceptualisation de connaissances. Car bien que les robots actuels soient capables de se déplacer, de manipuler des objets, d'interagir avec des êtres humains, ils restent avant tout des machines dont les capacités d'adaptation sont limitées particulièrement en ce qui concerne l'acquisition de nouvelles connaissances. Or, il semble inenvisageable, étant donné la diversité des situations auxquelles devront faire face ces robots, d'identifier et de programmer l'ensemble des solutions nécessaires à la bonne exécution des tâches auxquelles ils seront confrontés. Dans ce chapitre, je présenterai donc un système cognitif artificiel qui permet à un robot d'interpréter la perception de son environnement et de créer progressivement de nouveaux concepts. Une des originalités de ce travail est qu'il s'appuie aussi sur des fonctions cognitives permettant de modéliser les effets de la curiosité.

Le chapitre 6 me permettra ensuite d'introduire le concept de système cognitif distribué. Bien que l'idée d'un système cognitif distribué basé sur la théorie de l'énaction puisse sembler absurde dans le cas d'un système biologique, il n'en n'est pas de même pour un système artificiel. En effet, les technologies de l'information et de la communication offrent la possibilité de percevoir l'environnement et de contrôler des systèmes à distance. Les travaux présentés dans le chapitre 6 seront donc consacrés à la présentation d'un système cognitif distribué où les processus cognitifs conscients et inconscients peuvent être en partie dissociés et répartis sur des entités matérielles différentes distribuées dans l'espace.

1. http://www.bostondynamics.com/

Chapitre 4

Développement d'habiletés motrices

4.1 Introduction

Depuis le début des années 70, notamment à l'université de Waseda qui a conçu le premier robot humanoïde, le robot Wabot (WAseda roBOT) [1] [Kato 73], les recherches sur la conception et le contrôle de robots humanoïdes ont fait l'objet de nombreux travaux. Et bien qu'aujourd'hui certains prototypes comme par exemple les robots Asimo [Sakagami 02], HRP ([Hirukawa 04]), ou bien Nao [Gouaillier 09], prouvent la faisabilité technologique de telles machines, leurs performances restent très limitées notamment du point de vue de la locomotion, car la marche bipède, ce n'est pas simplement mettre un pied devant l'autre.

Les difficultés inhérentes au contrôle d'un bipède sont intimement liées à la structure mécatronique utilisée pour construire le robot. Généralement, l'approche la plus répandue consiste à utiliser une structure mécanique rigide à plusieurs degrés de liberté où l'ensemble des articulations sont commandées par des moto-réducteurs. Dans ce cas, les stratégies de contrôle, dont la plus répandue est celle proposée par Kajita [Kajita 09], permettent de générer les trajectoires articulaires du robot, via un modèle cinématique inverse, tout en assurant la stabilité du robot en maintenant la position du ZMP (Zero Moment Point) à l'intérieur de la surface de sustentation. Mais ces stratégies s'appuient sur une modélisation de la structure mécanique qui ne tient pas toujours compte de la complexité du système (pendule inversé, chariot sur une table). Et aujourd'hui, force est de constater que les performances des robots humanoïdes sont encore très inférieures à celles d'un être humain. Car si il est vrai que ces méthodes permettent tout de même de contrôler la marche de certains robots humanoïdes dans des conditions quasi-parfaites (marche lente, sol plat et régulier, pas d'obstacle), cela se complexifie dès

1. http://www.humanoid.waseda.ac.jp/booklet/kato_2.html

la prise en compte de certaines contraintes supplémentaires comme l'irrégularité du sol ou bien l'évitement d'obstacle. Ceci s'explique en partie par les limitations des caractéristiques dynamiques des moto-réducteurs (notamment en couple et accélération) ainsi que par la complexité des calculs à réaliser en temps réel. Pour ces raisons, de nombreuses études se sont focalisées sur des approches différentes que l'on pourrait qualifier de bio-inspirées. Ces solutions alternatives concernent aussi bien les aspects matériels (développement de muscles artificiels), que les aspects contrôles (utilisation de réseaux de neurones). Dans la suite de ce chapitre, seuls les aspects concernant la commande seront abordés.

Les travaux présentés dans ce chapitre, qui sont une contribution au développement de stratégies de contrôle bio-inspirées, s'inscrivent dans la continuité de ma thèse de doctorat dans laquelle j'ai abordé le contrôle d'un robot bipède sans pied, le robot RABBIT [2]. Les premiers travaux réalisés lors de ma thèse avaient notamment permis de valider une solution originale reposant sur l'utilisation d'un ensemble de réseaux de neurones pour la génération d'une marche stable complètement dynamique du robot RABBIT. C'est sur ces bases que nous nous sommes appuyés pour développer un système cognitif artificiel dédié à l'acquisition d'aptitudes motrices. L'originalité de ce travail consiste en une décomposition en deux parties du contrôle de la locomotion : la première pour la génération de mouvements de marche quasi-automatiques et la deuxième pour le contrôle de mouvements volontaires dans le cas par exemple de l'évitement d'un obstacle. Dans la suite de ce chapitre, après avoir énoncé les fondements de notre réflexion et situé nos travaux dans leurs contextes scientifiques, je présenterai le système cognitif artificiel que nous avons développé au LISSI. J'exposerai ensuite les résultats majeurs qui on été obtenus. Les travaux présentés ici ont, en partie, fait l'objet de la thèse de Weiwei YU et ont été notamment publiés dans [Sabourin 13] et [Madani 11].

4.2 Contexte scientifique

L'objectif de cette section est tout d'abord d'introduire les fondements « bio-inspirés » des travaux (section 4.2.1) qui seront présentés dans la section 4.3. Elle permettera aussi de positionner ces travaux par rapport à l'état de l'art (section 4.2.2).

4.2.1 Activité motrice et système nerveux central

Chez l'être humain, les mouvements sont le résultat d'un ensemble de contractions musculaires dont l'organisation, temporelle et spatiale, est orchestrée par le

2. http://www.gipsa-lab.grenoble-inp.fr/projet/Rabbit/

système nerveux central [Purves 04]. Ces activités motrices, coordination de mouvements simples qui repose en partie sur un répertoire inné de modèles [Rigal 02], sont le résultat d'un processus de développement et d'apprentissage qui s'échelonne sur plusieurs années. Ces activités motrices se décomposent en deux grandes catégories qui sont les aptitudes phylogénétiques, capacités spécifiques à l'espèce humaine comme la marche ou la course, et les aptitudes ontogéniques qui nécessitent un apprentissage particulier comme la nage ou le patinage. Les activités motrices de l'homme évoluent donc et s'enrichissent tout au long de sa vie en fonction de ses propres expériences, par transformation et adaptation de modèles de mouvements antérieurement acquis.

Le Système Nerveux Central (SNC) impliqué dans la génération des mouvements, et qui contrôle l'ensemble de l'activité musculaire, est composé de la moelle épinière, situé à l'intérieur de la colonne vertébrale, et de certaines parties du cerveau, principalement le tronc cérébral, le cervelet, les ganglions de la base ainsi que le cortex moteur. La figure 4.2.1 représente l'architecture, qui est communément admise dans la communauté scientifique, de la partie du système nerveux central impliquée dans le contrôle des mouvements des membres chez l'être humain. L'objectif ici n'est pas de décrire de manière précise le fonctionnement de cette partie du SNC qui fait encore l'objet de nombreuses recherches et débats, mais de mettre en évidence les aspects fonctionnels de cette structure. Ce SNC gère l'ensemble des activités motrices, de la plus simple à la plus complexe. Les motoneurones, qui sont situés dans la moelle épinière ainsi que dans le tronc cérébral, contrôlent l'activation des muscles. Ces motoneurones sont eux-même contrôlés par des circuits locaux, situés aussi dans la moelle épinière et le tronc cérébral. Ces circuits permettent de coordonner et réguler l'activité d'un groupe de motoneurones. Le cervelet, quant à lui, joue le rôle d'un asservissement en temps réel entre les mouvements réels et désirés [Purves 04]. Mais il intervient aussi sur le plus long terme permettant ainsi de réaliser un apprentissage moteur progressif. Le cortex moteur contrôle aussi les mouvements volontaires précis comme ceux par exemple des doigts. Les ganglions de la base joueraient quant à eux un rôle important dans le déclenchement des mouvements volontaires.

Il est important de remarquer que l'on peut différencier deux parties distinctes dans la structure du SNC qui jouent des rôles très différents. La première, la partie basse, composée de la moelle épinière et du tronc cérébral, permet à priori de générer un contrôle moteur primaire. La deuxième partie, la partie haute, composée du cortex, du cervelet, et des ganglions de la base, permet quant à elle d'initier les mouvements, de les coordonner ainsi que de les apprendre. Des expériences chez des animaux vertébrés, notamment les chats, ont montré que après une lésion entre la

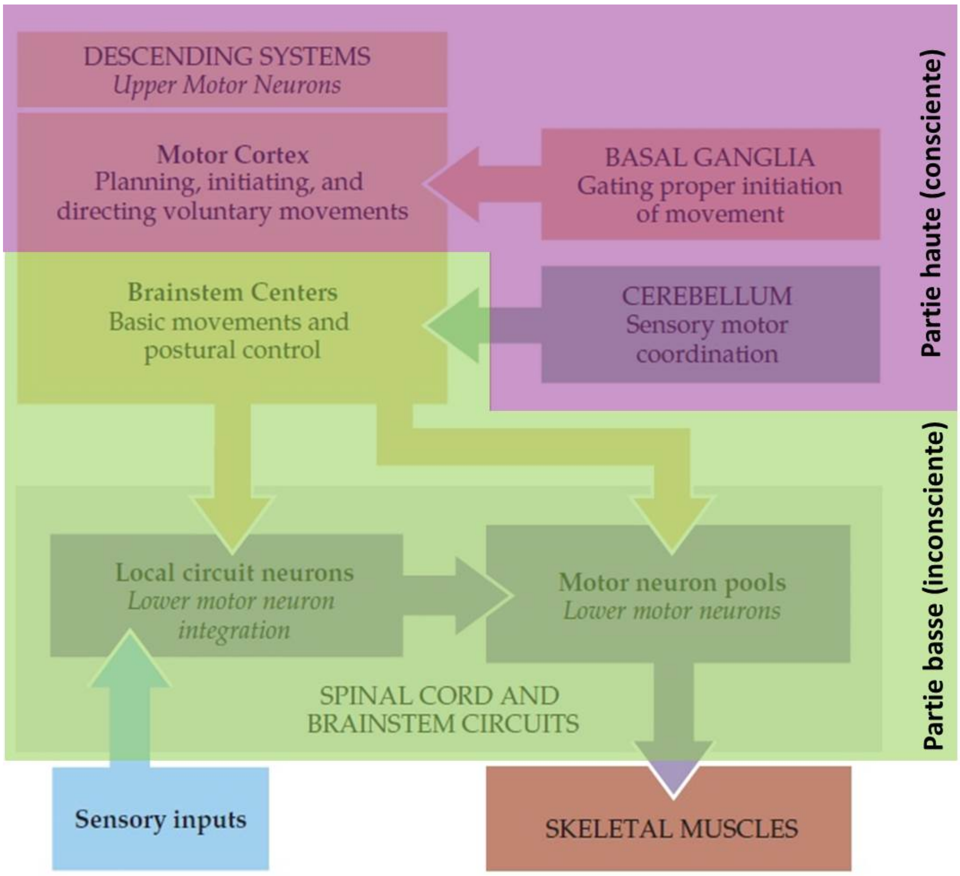

FIGURE 4.2.1: Organisation d'ensemble des structures nerveuses impliquées dans le contrôle des mouvements. Quatre systèmes distincts - les circuits locaux de la moelle épinière et du tronc cérébral, les voies modulatrices descendantes, les ganglions de la base et le cervelet - contribuent au contrôle moteur (Extrait et adapté de [Purves 04], p372).

moelle épinière et l'encéphale, ces animaux conservaient la possibilité de générer des mouvements en réponse à leurs stimulus [Whelan 96]. Les chats décérébrés conservent donc des activités motrices plus ou moins élaborées en fonction du type de la lésion mais ils perdent toute possibilité d'ajuster leurs mouvements comme par exemple d'éviter un obstacle. Il est cependant important de remarquer que ces résultats ne sont pas directement transposables à l'homme. En effet, un paraplégique conserve la possibilité de générer (sous stimulation) des mouvements très primaires, mais ces mouvements sont considérablement moins efficaces que ceux observés chez le chat. Le SNC d'un être humain est plus complexe que celui d'un chat, de même que le SNC d'un chat est plus complexe que celui d'une lamproie. Cependant, le point commun entre les animaux vertébrés, comme le chat, et les êtres humains est qu'il est possible d'identifier deux parties distinctes, l'une que l'on pourrait qualifier d'inconsciente et qui peut fonctionner de manière quasi-autonome (sous l'effet de certaines stimulations) mais sans l'intervention par exemple du cortex moteur, et l'autre que l'on peut qualifier de consciente pour le contrôle des mouvements volontaires ou d'activités motrices.

4.2.2 Approche bio-inspirée pour le contrôle de la locomotion en robotique

Du point de vue de la commande, les recherches bio-inspirées en robotique se sont essentiellement concentrées sur la conception de CPG (Central Pattern Generator [3]) artificiels. Ces CPG ont été clairement identifiés chez certains animaux comme la lamproie. De manière plus générale, les CPG peuvent être assimilés aux circuits locaux et aux motoneurones de la moelle épinière et du tronc cérébral (voir Fig. 4.2.1). Une très bonne synthèse des recherches concernant les CPG est disponible dans [Ijspeert 08]. Les CPG artificiels sont généralement basés sur des architectures à réseaux de neurones interconnectés qui sont capables de générer intrinsèquement des trajectoires cycliques stables (neuro-oscillateurs). Un des précurseurs dans l'utilisation de ces neuro-oscillateurs en locomotion bipède est très certainement Taga [Taga 91] qui a proposé un CPG basé sur le modèle neuronal de Matsuoka [Matsuoka 85]. Le modèle de Mastsuoka est constitué de deux neurones capables de s'inhiber mutuellement. Lorsque l'entrée du réseau est nulle, le réseau oscille librement à sa fréquence naturelle. Mais lorsqu'on applique un signal d'entrée d'amplitude suffisante et dont la fréquence est proche de la fréquence naturelle, le réseau à tendance à osciller à la même fréquence que le signal d'entrée. L'amplitude de sortie du signal est ajustable via un paramètre de « tonicité » (tonic input). Les sorties des deux neurones sont utilisées directement pour

3. « Central Pattern Generator » est le terme anglais souvent utilisé mais qui pourrait être traduit en français par « générateur spinal locomoteur » ou « générateurs centraux de rythme »

commander des muscles artificiels. Il est aussi possible de faire la différence entre ces deux sorties pour générer des trajectoires articulaires. Dans ce cas, le suivi des trajectoires désirées est assuré par des contrôleurs, par exemple, de type PID.

Dans la solution proposée par Taga [Taga 91], chaque articulation (chevilles, genoux et hanches) est contrôlée par deux neurones. Un neurone est destiné a commander le muscle extenseur, et l'autre le fléchisseur. L'amplitude de chaque couple moteur est directement proportionnelle à la sortie d'un neurone. Cette structure neuronale est complétée par des boucles de retour sensorielles permettant de synchroniser l'activité rythmique (alternance de phases d'appui avec des phases d'oscillation) de la marche. Les résultats obtenus en simulation montrent que cette stratégie permet de contrôler la marche d'un bipède dans le plan (plan sagittal). Par la suite, ces travaux ont été étendus au contrôle d'un robot bipède 3D mais en utilisant une paire de neurones supplémentaires pour ajuster la position du tronc dans le plan latéral [Ishiguro 03]. Dans [Miyakoshi 98], les auteurs ont aussi proposé une alternative permettant de réduire le nombre de paires de réseaux (trois paires de neurones dans ce cas précis). Un réseau permettait de commander le tronc au niveau de la taille, les deux autres étaient dédiés aux contrôles des mouvements des pattes du robot. Dans [Endo 05], Endo a quant à lui utilisé seulement deux paires de neurones, une paire de neurones pour les mouvements des pattes du robot dans le plan sagittal et l'autre pour le plan vertical. Le réglage des paramètres de ce réseau par apprentissage a ensuite été proposé dans [Endo 08]. Cette approche a aussi fait l'objet d'une validation expérimentale sur le robot QRIO. Des approches avec des neuro-oscillateurs différents ont aussi été proposées, comme par exemple l'oscillateur de Hopf [Righetti 06], ou bien des contrôleurs utilisant des fonctions sinusoïdales [Morimoto 08].

Si aujourd'hui comme nous venons de le voir, des solutions bio-inspirées ont fait déjà l'objet de nombreuse études, elles sont généralement restées cantonnées à la génération de mouvements rythmiques. La génération de mouvements complexes comme l'évitement d'obstacle n'a, à notre connaissance, jamais été étudiée. L'objectif de la section suivante a donc pour but, de présenter les fondements théoriques d'une solution alternative, basée sur la conception d'un système cognitif artificiel, dédié spécialement à la locomotion bipède, qui intègre des processus cognitifs inconscients, modélisant la partie CPG du SNC pour la génération de mouvements de marche quasi-automatique et des processus cognitifs conscients, lors de contrôle de mouvements volontaires.

4.3 Système cognitif artificiel dédié à l'acquisition de la locomotion bipède

Les différentes activités motrices chez l'homme consistent en un apprentissage de la coordination de mouvements primaires permettant d'atteindre l'objectif désiré (marche, course, activités sportives, etc..). Les générateurs centraux de rythme, plus connus sous le nom de Central Pattern Generators (CPG), sont responsables des activités motrices primaires, et le cerveau permet progressivement de coordonner l'ensemble de ces activités primaires afin de construire des activités motrices quasi-automatiques. Ce processus de construction d'activités motrices est similaire que cela soit des d'aptitudes phylogénétiques, comme la marche, ou bien que cela concerne les aptitudes ontogéniques dans le cas de l'acquisition et de l'amélioration du geste sportif [Collet 01]. L'hypothèse que le système nerveux central peut se décomposer en deux grandes parties est donc plausible : une partie « inconsciente » responsable des activités quasi-automatiques mais qui reste sous le contrôle de la partie « consciente » dont le rôle est de pourvoir « programmer » ou « reprogrammer » les programmes moteurs des différentes aptitudes motrices. La partie consciente a aussi pour rôle d'adapter, en temps réel, les différentes stratégies motrices en fonction de l'environnement. C'est à partir de ces hypothèses que nous avons choisi de développer une approche originale qui repose sur la conception d'un système cognitif artificiel destiné au contrôle de la locomotion de robots bipèdes.

Le modèle bipède pris comme support de cette étude correspond à celui du robot RABBIT [Chevallereau 00]. Ce robot, sans pied, ne possède que 4 degrés de liberté et ses mouvements sont limités dans le plan sagittal. La surface d'appui entre la patte du robot et le sol se limitant (théoriquement) à un point de contact, RABBIT a la particularité de marcher dynamiquement. La figure 4.3.1 schématise la structure de ce robot. Les différents angles et vitesses articulaires sont supposés accessibles via des capteurs ainsi qu'une information binaire permettant de déterminer si le pied est en contact avec le sol, la vitesse moyenne du robot est quant à elle calculée en faisant le rapport entre la longueur du pas et la durée d'un pas à chaque phase de double support (équation 4.3.1).

$$V_{step} = \frac{L_{step}}{T_{step}} \tag{4.3.1}$$

La jambe en phase d'appui est toujours considérée comme un segment rigide (le genou de la patte en appui avec le sol est « bloqué » pendant toute la phase de support). Sous l'effet de la dynamique de la structure mécanique, qui peut être modélisée par un pendule inverse, le bassin décrit une trajectoire circulaire dont le centre est le point de contact avec le sol. Lors de cette phase de simple support, la

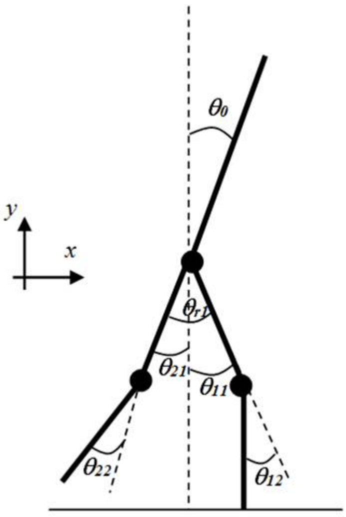

FIGURE 4.3.1: Schématisation du robot bipède sans pied à 4 degrés de liberté dont les mouvements sont limités dans le plan sagittal.

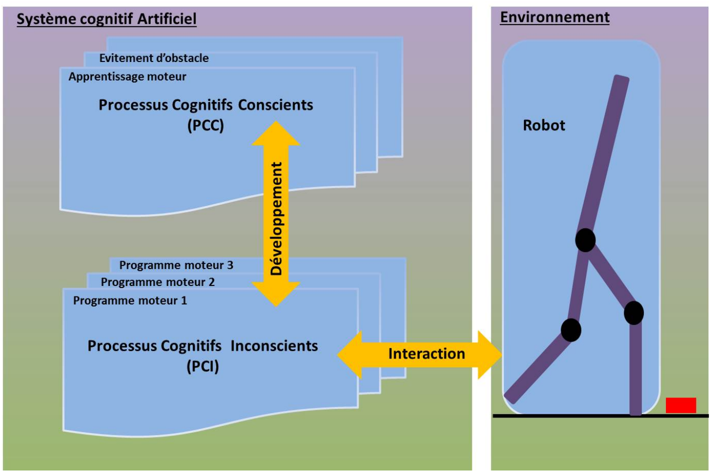

FIGURE 4.3.2: Illustration fonctionnelle du système cognitif artificiel appliqué au contrôle de la locomotion bipède. Une partie du SCA regroupe les PCI qui concernent le contrôle des activités motrices quasi-automatiques et l'autre les PCC pour le contrôle des mouvements volontaires. Le SCA peut interagir avec son environnement grâce à la structure mécatronique du robot.

jambe en phase d'oscillation doit progressivement passer de l'arrière vert l'avant du robot.

Le SCA, schématisé par la figure 4.3.2, se compose de deux parties : la première regroupe les PCI (Processus Cognitifs Inconscients) qui concernent le contrôle des activités motrices quasi-automatiques et la deuxième les PCC (Processus Cognitifs Conscients) pour le contrôle des mouvements volontaires. Les PCI correspondent à un ensemble de programmes moteurs primaires permettant de générer les trajectoires articulaires de la jambe en phase d'oscillation. Les PCC ont pour but d'adapter les trajectoires articulaires du robot en fonction de l'objectif à atteindre (vitesse moyenne désirée, évitement d'obstacle, etc..). Le SCA peut interagir avec son environnement grâce à la structure mécatronique du robot qui joue ici le rôle du système musculo-squelettique de l'homme. Dans la suite de cette section, je présenterai donc les aspects algorithmiques du SCA qui reposent sur l'utilisation des techniques de « soft-computing » et plus particulièrement les réseaux de neurones CMAC, la logique floue, ainsi que l'apprentissage par renforcement. Je commencerai par introduire succinctement les réseaux de neurones CMAC proposés initialement par Albus (section 4.3.1), puis je présenterai les PCI (activités motrices quasi-automatiques) qui s'appuient sur une extension du CMAC de type neuro-flou : l'architecture FuzzyCMAC (section 4.3.2). Enfin, je montrerai qu'il est possible d'utiliser des procédures d'apprentissage par renforcement afin d'optimiser les règles de ce système neuro-flou (section 4.3.3), ce qui constituera la base de nos PCC (contrôle des mouvements volontaires, création de nouvelles aptitudes motrices).

4.3.1 Cerebellar Model Articulation Controller (CMAC)

Dans les années 70, James Albus fut le premier à proposer le contrôle d'un bras manipulateur à l'aide d'un réseau de neurone qu'il nomma CMAC (Cerebellar Model Articulation Controller) [Albus 75]. L'originalité du CMAC est que sa structure s'inspire du cervelet. Et comme nous le verrons par la suite, ce réseau de neurones possède certains avantages. Aujourd'hui le CMAC est donc un réseau de neurones à part entière qui a fait l'objet de nombreuses études aussi bien du point de vue théorique que du point de vue applicatif [Sabourin 13]. Le CMAC a notamment été utilisé en robotique pour la génération de trajectoires [Benbrahim 97] [Sabourin 05] [Kim 00].

Le CMAC est un réseau de neurones de type mémoire associative. Il est constitué d'un ensemble de N_d capteurs binaires répartis sur N_l couches. Bien que je présente ici un CMAC avec une entrée et une sortie (SISO, Single Input Single Output), il est possible de généraliser ce réseau à un système multi-entrées (MISO,

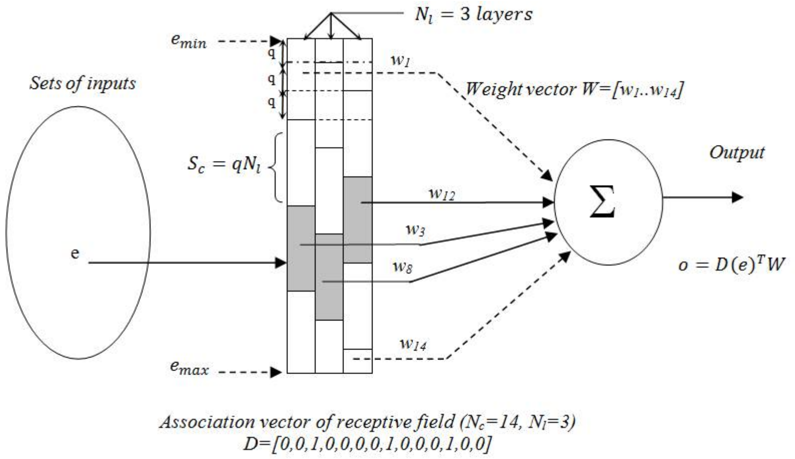

FIGURE 4.3.3: Description d'un réseau de neurones CMAC constitué de 14 récepteurs répartis sur 3 couches.

Multi-Input Single Output). La figure 4.3.3 montre une organisation simplifiée d'un CMAC SISO de 14 récepteurs ($N_d = 14$) régulièrement distribués sur 4 couches ($N_l = 4$). Lorsque le signal d'entrée e est compris dans l'intervalle du champ réceptif d'un capteur S_c, sa sortie vaut 1 sinon elle reste égale à 0. Sur chaque couche, les champs réceptifs sont décalés d'un pas de quantification q. Le nombre de détecteurs dépend d'une part de la largeur du champ réceptif et d'autre part du nombre de couches. Et étant donné qu'il y a des chevauchements entre les récepteurs de différentes couches, des valeurs d'entrées proches activeront des détecteurs communs (généralisation locale). La sortie d'un CMAC est calculée en deux temps. La première consiste à déterminer les valeurs du vecteur $D = [d_1, ...d_i, ..d_{Nd}]$; où les valeurs binaires d_i sont égales à 1 si le récepteur est activé et égales à 0 dans le cas contraire. La seconde étape consiste à calculer le produit scalaire (équation 4.3.2) entre le vecteur D et le vecteur W contenant les poids associés à chaque capteur. Pendant la phase d'apprentissage, les poids du CMAC sont modifiés en utilisant l'équation 4.3.3. $W(t)$ et $W(t+1)$ sont respectivement les vecteurs poids avant et après la mise à jour pour chaque itération, β est un paramètre permettant de moduler le taux d'apprentissage et est compris entre $[0, 1]$, O^d la sortie désirée et O la sortie réelle du CMAC.

$$O = D(e)^T W \tag{4.3.2}$$

$$W(t+1) = W(t) + \frac{\beta(O^d - O)}{N_l} \tag{4.3.3}$$

Les principaux avantages de ce réseau de neurones sont les suivants :

– le nombre d'opérations nécessaires pour déterminer la valeur de sortie du réseau est relativement limité. En effet, le CMAC est un réseau de neurones à généralisation locale ce qui signifie qu'une petite partie de l'ensemble des poids du réseau intervient dans le calcul de la sortie ce qui permet ainsi de réduire le temps de calcul en comparaison avec d'autres réseaux de neurones.
– il est possible de l'implémenter aussi bien de manière « soft » que « hard » (notamment sous la forme d'un FPGA). A noter qu'une implémentation « hard » permet de bénéficier, en terme de calculs, de l'avantage du parallélisme.

Ces deux avantages permettent d'utiliser les CMAC dans des d'applications temps réel. Mais bien que le CMAC SISO possède des atouts certains, un CMAC a plusieurs entrées tend à perdre le bénéfice des avantages cités précédemment. Pour ces raisons, nous avons proposé une nouvelle structure qui utilise la combinaison d'un Système d'Inférence Floue (SIF) et d'un ensemble de CMAC SISO, ce qui constituera par la suite la base des processus cognitifs inconscients destinés au contrôle moteur.

4.3.2 Processus cognitifs inconscients

L'objectif des PCI est de fournir des programmes moteurs permettant au robot de marcher de manière quasi-automatique. Pour cela, nous avons choisi d'utiliser un FuzzyCMAC. Cette structure est relativement bien adaptée à notre application car elle permet de générer une « infinité » de trajectoires (mouvements) à partir d'un ensemble limité de trajectoires de références. En effet, la sortie d'un FuzzyCMAC est obtenue en calculant la moyenne pondérée de l'ensemble des k sorties des $CMAC_k$ (la sortie d'un SIF de type Takagi-Sugeno correspond au barycentre des conclusions des règles pondérées par les valeurs de vérité des règles activées ([Glorennec 99]).

La figure 4.3.4 représente la description schématique d'un FuzzyCMAC. Le signal d'entrée e ($e \in R$) est appliqué à l'ensemble des k réseaux de neurones $CMAC_k$ (k $\in [1., .., N_c]]$. La sortie de chaque réseau est calculée à l'aide de l'équation 4.3.4. D_k et W_k sont respectivement le vecteur binaire de l'état des capteurs et le vecteur poids de chaque $CMAC_k$.

$$O_k = D_k(e)^T W_k \tag{4.3.4}$$

Le vecteur d'entrée $X = [x_1, .., x_n]$ correspond quant à lui aux entrées du système d'inférences floues. La sortie du FuzzyCMAC est calculée conformément à la méthode de Takagi-Sugeno. On commence donc par déterminer le degré d'appartenance $\mu_{A_i^j}$ de chaque entrée x_i ($i = [1, .., N_i]$) aux différents ensembles flous ($j = [1, .., N_j]$). Le calcul de la sortie est ensuite déterminé à l'aide de l'équation

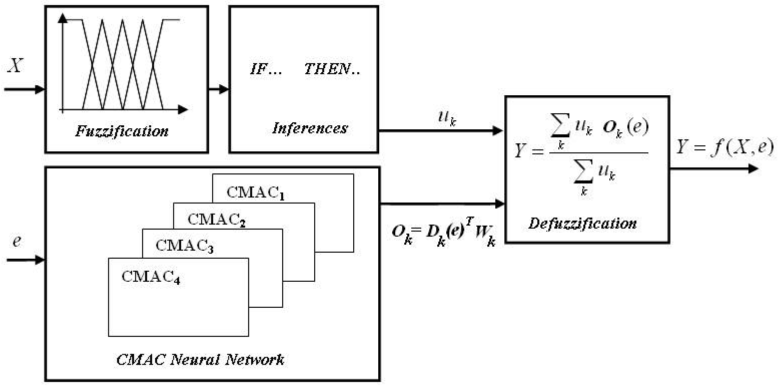

FIGURE 4.3.4: Schéma descriptif d'un FuzzyCMAC. La sortie du FuzzyCMAC est obtenue en calculant la moyenne pondérée de l'ensemble des sorties du $CMAC_k$

4.3.5 (avec $u_k = \prod \mu_{A_i^j}$).

$$Y = \frac{\sum_k u_k \; O_k(e)}{\sum_k u_k} \tag{4.3.5}$$

La figure 4.3.5 représente, quant à elle, l'ensemble du CPG. A chaque articulation correspond un FuzzyCMAC qui génère la trajectoire désirée (θ_{ij}^d) en fonction de l'entrée $e = \theta_{i1}$. Cela signifie que l'on peut générer une trajectoire adaptable à partir d'un ensemble relativement limité de trajectoires de références. Et afin d'obtenir un mouvement quasi-automatique, l'entrée e de ces programmes moteurs primaires est l'angle défini par l'écart entre la jambe en appui et la verticale (θ_{11} dans le cas de la figure 4.3.5). On peut considérer cet angle (θ_{i1}) comme un retour sensoriel permettant d'asservir la position de la jambe en phase d'oscillation avec le positionnement du bassin pendant un cycle de marche. Par conséquent, contrairement aux différentes approches généralement utilisées en robotique, les trajectoires articulaires ne sont pas régies par une variable temporelle mais dépendent d'un paramètre géométrique. De plus, le contrôle de la vitesse moyenne est effectué automatiquement via un ajustement de l'inclinaison du tronc. Le système, à chaque pas, calcule la différence entre la vitesse moyenne désirée et la vitesse moyenne réelle obtenue avec l'équation 4.3.1. L'angle désiré q_0 est ensuite ajusté par un algorithme similaire à un proportionnel dérivé [Sabourin 07]. Il faut toutefois noter que cet ajustement intervient à chaque pas et non pas en continu. C'est donc un processus discret. Une des particularités de notre solution est donc que la partie qui regroupe les processus cognitifs inconscients peut fonctionner indépendamment des PCC. Par analogie avec un système biologique, la partie qui regroupe les PCI est équivalente à la partie basse du SNC associée au contrôle des

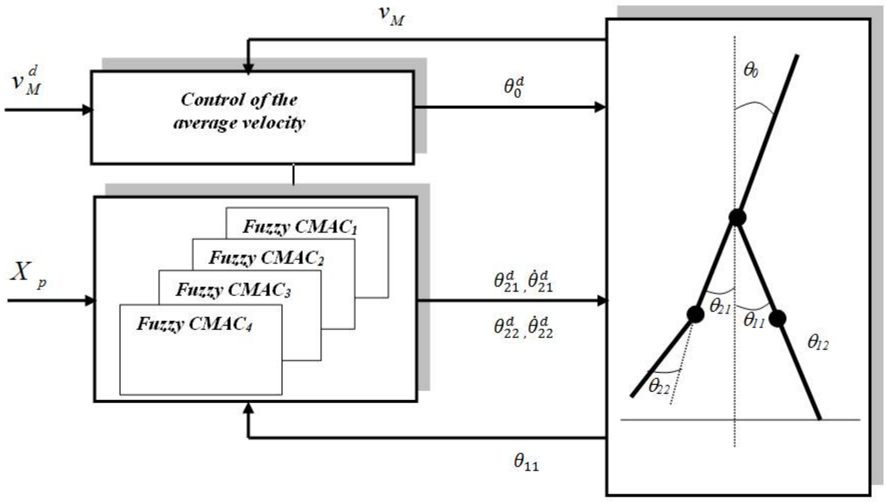

FIGURE 4.3.5: Représentation schématique du CPG fondé sur l'utilisation du FuzzyCMAC.

activités motrices (voir figure 4.2.1).

4.3.3 Processus cognitifs conscients

Les processus cognitifs conscients nécessitent de créer ou modifier les règles flous. Aujourd'hui, il existe de nombreuses méthodes permettant de changer, d'optimiser, par apprentissage ces règles floues ([Glorennec 99]). Dans notre cas, la solution qui a retenu notre attention repose sur l'utilisation du Q-learning [Watkins 92]. Cette technique, que l'on nomme Fuzzy Q-learning est donc une extension du Q-learning et permet de sélectionner, pour chaque règle, la meilleure conclusion [Glorennec 97]. Un processus d'apprentissage, similaire au Q-learning, permet de faire évoluer les fonctions qualités. A la fin de la séquence d'apprentissage, les conclusions choisies pour chaque règle sont celles dont la valeur de la fonction qualité est la plus élevée. La base initiale du système d'inférence floue est donc composée d'un ensemble de règles comme celle décrite par l'équation 4.3.6 :

$$IF\ x_1\ is\ M_1^1\ AND\ x_i\ is\ M_i^j\ THEN \begin{cases} & y_k = a_k^1 \quad \text{with} \quad q = q_k^1 \\ \text{or} & y_k = a_k^l \quad \text{with} \quad q = q_k^l \\ \text{or} & y_k = a_k^{N_l} \quad \text{with} \quad q = q_k^{N_l} \end{cases} \tag{4.3.6}$$

x_i $(i = 1..N_i)$ représente les entrées du SIF, N_i correspond à la dimension de cet espace d'entrée. Chaque ensemble flou j pour l'entrée i est modélisé par une fonction d'appartenance A_i^j avec μ_i^j sa valeur d'appartenance correspondante ($\mu_i^j =$

$A_i^j(x_i)$). a_k^l et q_k^l sont respectivement les l^{th} possibles conclusions pour chaque règle k et les valeurs qualités correspondantes ($k = 1..N_k$; $l = 1..N_l$). A chaque itération de la phase d'apprentissage, un agent observe l'état du système. Pour chaque règle (ou du moins celles qui sont activées dans l'état observé), le système d'apprentissage doit, à partir de sa politique d'exploration, choisir une action a_k^l parmi les N_l actions. La sortie du système flou est calculée à partir des conclusions qui ont été sélectionnées dans l'état observé (équation 4.3.7). L'équation 4.3.8 permet de mettre à jour les valeurs qualités des actions sélectionnées avec $\alpha_k(t) = \mu_1^j\ \mu_2^j................\mu_{Ni}^j$. A l'état suivant, l'agent met à jour, pour chaque règle activée, les valeurs Δq_k^l de la matrice qualité Q (équation 4.3.9).

$$Y(t) = \sum_{k=1}^{N_k} \alpha_k(t) a_k^l(t) \tag{4.3.7}$$

$$Q(t) = \sum_{k=1}^{N_k} \alpha_k(t) q_k^l(t) \tag{4.3.8}$$

$$\Delta Q(t) = \beta[r + \gamma \sum_{k=1}^{N_k} \alpha_k(t+1) max(Q_k^l(t+1)) - Q(t)] \tag{4.3.9}$$

Par conséquent, le Fuzzy Q-learning est un extracteur de connaissances permettant de choisir les meilleures règles dans une base de règles préétablies. En modifiant les règles du FuzzyCMAC (section 4.3.2), le Fuzzy Q-learning nous permettra donc de modifier les trajectoires articulaires et par conséquent adapter l'allure de marche du robot dans la cas d'une tâche d'évitement d'obstacle par exemple. En résumé, la partie qui regroupe les processus cognitifs conscients peut contrôler les PCI en les modifiant ou bien en en créant de nouveaux. Par analogie avec un système biologique, la partie qui regroupe les PCC est équivalente à la partie haute du système nerveux central associée au contrôle des activités motrices (voir figure 4.2.1).

4.4 Principaux Résultats

Afin d'illustrer l'approche précédemment décrite, je vais maintenant exposer deux exemples qui illustreront le fonctionnement de ce système cognitif artificiel. Le premier exemple concerne l'adaptation de l'allure en fonction de la vitesse moyenne de déplacement du robot (section 4.4.1). Le second exemple concerne l'évitement dynamique d'un obstacle (section 4.4.2). Dans ce dernier cas, l'utilisation des fonctions cognitives conscientes est indispensable pour que le robot planifie une stratégie d'évitement.

4.4.1 Génération de trajectoires adaptatives

Chez l'Homme, la longueur de pas augmente progressivement et naturellement en fonction de la vitesse moyenne de déplacement. Au-delà d'une certaine limite, la longueur de pas se stabilise et l'augmentation de la vitesse moyenne est uniquement liée à l'accroissement de la cadence des foulées. Dans le cas de l'utilisation du FuzzyCMAC présenté à la section 4.3.2, la production des trajectoires est le résultat d'une fusion de plusieurs sorties de réseaux de neurones CMAC. En utilisant la vitesse moyenne réelle du robot comme entrée du système d'inférence floue ($X = V_M$, V_M étant définie par l'équation 4.3.1), la longueur de pas s'ajuste automatiquement en fonction de la vitesse de progression V_M. Le tableau 4.2 donne les valeurs numériques permettant de caractériser 5 allures de marches qui serviront de références dans notre exemple.

Gait	L_{step}(m)	T_{step}(s)	V_M(m/s)
$Gait^1$	0,24	0,6	0,4
$Gait^2$	0,3	0,6	0,5
$Gait^3$	0,34	0,567	0,6
$Gait^4$	0,38	0,543	0,7
$Gait^5$	0,43	0,543	0,8

Table 4.1: Longueur et durée des foulées en fonction des allures de marche.

Chaque allure de marche est définie par une longueur de pas (L_{step}) ainsi que par la durée du pas (T_{step}). A chaque allure de marche correspond des CMAC spécifiques. Chaque fuzzyCMAC est donc composé d'un ensemble de réseaux de neurones (5 dans cet exemple) et d'un système d'inférence flous, dont les fonctions d'appartenance et les règles sont représentées sur la figure 4.4.1. La figure 4.4.2 illustre le résultat d'une simulation où la vitesse moyenne désirée V_M^d est modifiée. Au début de la simulation, $V_M^d = 0,4m/s$ puis passe brusquement à $1m/s$. Progressivement, le tronc va s'incliner alors vers l'avant afin de composer la différence entre la vitesse réelle V_M et la vitesse désirée V_M^d. La vitesse moyenne augmentant progressivement, ceci va entraîner un allongement automatique de la longueur de pas. Bien que l'augmentation de la vitesse moyenne désirée V_M^d peut être assimilée à un processus cognitif volontaire, l'adaptation des trajectoires articulaires s'effectue de manière quasi-automatique. C'est donc le résultat d'un processus cognitif inconscient.

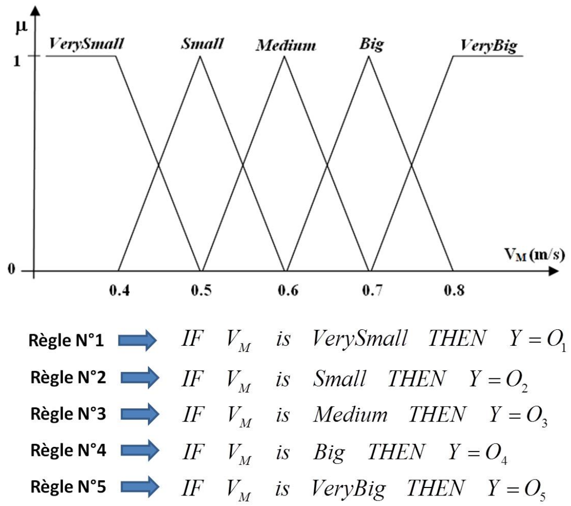

FIGURE 4.4.1: Fonctions d'appartenance et règles floues utilisées pour moduler la longueur de pas en fonction de la vitesse moyenne.

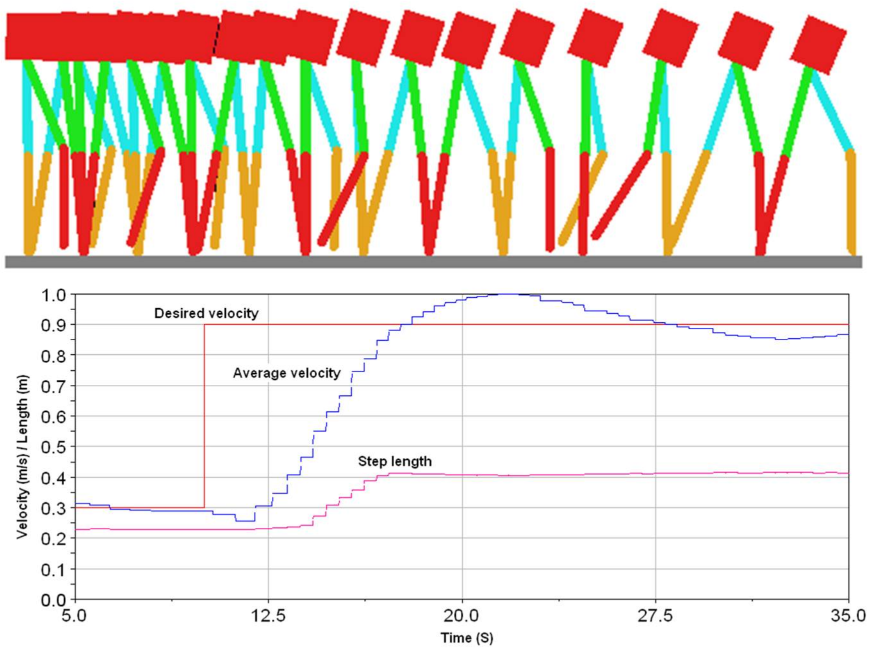

FIGURE 4.4.2: Illustration de la modification de l'allure de marche lorsque la vitesse moyenne augmente.

4.4.2 Évitement dynamique d'obstacle

Si généralement, la marche chez l'Homme est le résultat d'une activité motrice quasi-automatique, un être humain est parfois obligé d'établir des stratégies particulières face à certaines difficultés. C'est notamment le cas lors de l'évitement ou du franchissement d'un obstacle. La solution à ce genre de problème est généralement fondée sur l'élaboration d'une planification et nécessite l'utilisation de processus cognitifs conscients. Dans ce paragraphe, je montre que les bases mathématiques du SCA présentées précédemment permettent d'apporter une solution très concrète à cette problématique. Les spécificités et restrictions de l'exemple qui va suivre sont :

- Le robot bipède avance dans le plan sagittal. Il a la capacité d'adapter son allure de marche (durée et longueur de pas). Les phases de double support sont considérées instantanées (le basculement entre phase d'appui et phase d'oscillation est instantanée).
- La largeur de l'obstacle à enjamber est toujours inférieure à la longueur de pas maximum du robot (environ $0,4m$), sa hauteur quant à elle est considérée nulle (obstacle plat). La vitesse de l'obstacle est constante pendant toute la durée de la simulation.
- Le robot se déplace vers l'obstacle qui peut être statique (sa vitesse de déplacement est nulle) ou bien dynamique. Les vitesses moyennes du robot et de l'obstacle sont calculées à chaque phase de double support.

Le problème revient donc à trouver une succession de pas (durée et longueur) adéquate afin d'éviter que :

- la patte du robot en phase d'oscillation ne touche pas l'obstacle lors de la prise d'appui (Fig. 4.4.3-a),
- lorsque l'obstacle est dynamique, celui-ci ne vient pas percuter la patte du robot en phase d'appui (Fig. 4.4.3-b).

Dans tous les cas, si il y a un contact entre l'obstacle et le robot, c'est un échec et on considère que le robot n'a pas pu l'éviter. Par contre, si le robot arrive à enjamber correctement l'obstacle sans qu'il y ait eu contact, alors c'est une réussite.

Comme je l'ai écrit précédemment, le Fuzzy Q-learning consiste à optimiser, par des techniques de renforcement, un système d'inférences floues en modifiant la partie conclusion de chaque règle. Cela revient donc à trouver une adéquation entre les règles du SIF et les allures de marche qui sont caractérisées par des durées et des longueurs de pas. En se basant sur le SIF présenté précédemment et en prenant la vitesse de l'obstacle (v_{obs}) et la distance entre le robot et l'obstacle (d_{obs}) comme entrées du SIF, on construit alors un ensemble de règles du type :

$$IF\ v_{obs}\ is\ M_1^i\ AND\ d_{obs}\ is\ M_1^j\ THEN\ y = Gait^k \tag{4.4.1}$$

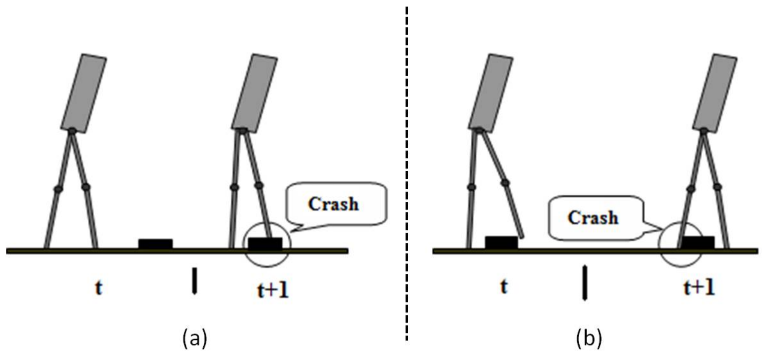

FIGURE 4.4.3: Exemples de cas où le robot touche un obstacle : la patte en phase d'oscillation vient toucher l'obstacle (a), l'obstacle vient percuter la patte en appui avec le sol (b).

M_1^i et M_1^j sont respectivement les fonctions d'appartenance, représentées sur la figure 4.4.4, des ensembles flous des entrées v_{obs} et d_{obs}. Au total, nous avons donc 15 règles (ce nombre de règles correspondant au produit des nombres de fonctions d'appartenances des entrées $v_{obs} \in [0..0,3]$ et $d_{obs} \in [1..1,2]$).

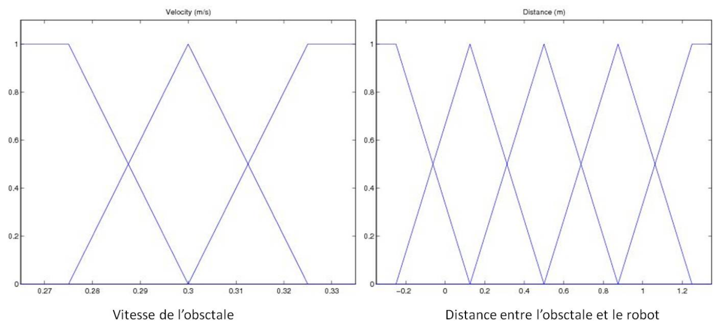

FIGURE 4.4.4: Fonctions d'appartenances utilisées pour la vitesse de l'obstacle ($v_{obs} \in [0..0,3]$) et la distance entre le robot et l'obstacle ($d_{obs} \in [1..1,2]$).

Dans ce contexte, la solution au problème posé repose sur l'utilisation d'un « émulateur » capable de simuler la progression, dans le temps et l'espace, du robot dans son environnement. Ce simulateur doit notamment permettre de connaître à chaque pas (chaque itération) les positions (dans l'espace et dans le temps) des pieds du robot ainsi que celle de l'obstacle. Cette modélisation numérique est donc discrète dans le sens où les donnés sont mises à jour à chaque phase de double appui et elles ne nécessitent pas la prise en compte de la dynamique réelle du robot. Le processus d'apprentissage se déroule sur plusieurs essais d'évitement. Chaque essai représente une succession de pas (un pas correspond à une itération) du cycle d'évitement d'obstacle complet. A chaque itération, le système à partir du FuzzyCMAC calcule la longueur et la durée des pas du bipède. La position des pieds du robot ainsi que celle de l'obstacle sont ensuite mises à jour dans le simulateur. Un essai est terminé lorsque le robot a évité l'obstacle (succès) ou bien a percuté l'obstacle (échec). A chaque itération, un signal de renforcement est envoyé afin d'évaluer les performances des règles utilisées. Lorsque cette phase d'apprentissage est terminée, il est alors possible d'utiliser les règles trouvées pour contrôler le robot « réel ». Les résultats qui suivent illustrent l'évitement d'un obstacle dynamique de $0,1m$ de largeur se déplaçant à une vitesse de $0,3m/s$. Le tableau 4.2 donne la solution qui a été trouvée dans cet exemple et la figure 4.4.5 représente la solution fournie par le simulateur. La figure 4.4.6 représente le résultat de la simulation lorsque les règles sont utilisées pour contrôler le robot.

V_{obs} / d_{obs}	Small	Medium	Big
Very Small	$Gait^3$	$Gait^3$	$Gait^3$
Small	$Gait^5$	$Gait^4$	$Gait^1$
Medium	$Gait^5$	$Gait^2$	$Gait^1$
Big	$Gait^3$	$Gait^3$	$Gait^3$
Very Big	$Gait^5$	$Gait^5$	$Gait^5$

Table 4.2: Règles utilisées par le SIF après apprentissage

4.5 Conclusion

Dans ce chapitre, j'ai présenté un système cognitif artificiel dédié au contrôle de la locomotion d'un robot bipède dans le plan sagittal. Ce système est constitué de processus cognitifs inconscients modélisant la partie CPG du SNC pour la génération de mouvements de marche quasi-automatiques et de processus cognitifs conscients pour le contrôle de mouvements volontaires. Bien que ce chapitre se soit focalisé sur les processus cognitifs dédiés à l'acquisition de la marche bipède, il est important de signaler que d'autres fonctions cognitives jouent aussi des rôles essentiels dans l'acquisition d'activités motrices. La perception de l'environnement via l'utilisation d'un système de vision en est un bon exemple car il permet d'apprécier les dimensions et les trajectoires d'obstacles à éviter. Enfin, si le champ applicatif de cette étude se limite ici à la marche d'un bipède dans le plan, cette approche peut à priori être étendue à d'autres aptitudes motrices. Une des pers-

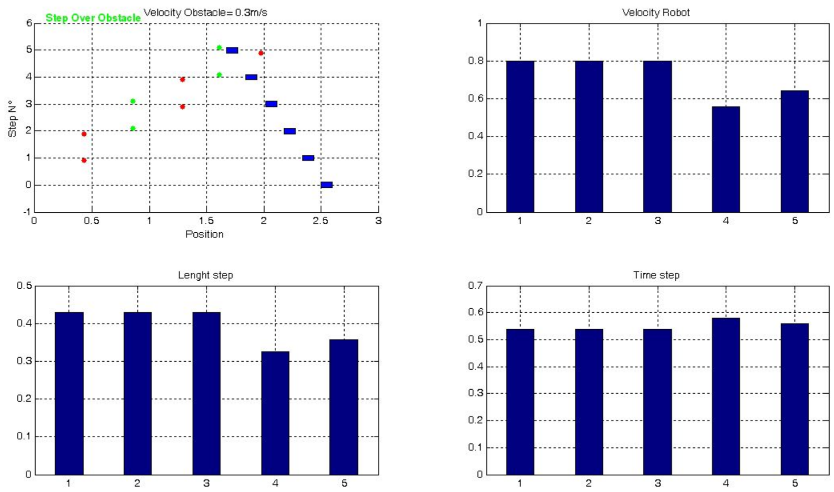

FIGURE 4.4.5: Illustration des résultats donnés par le simulateur en utilisant le SIF du tableau 4.2. L'obstacle de 0,1m de largeur se déplace en direction du robot. Les points rouges et verts représentent respectivement les positions des pieds gauche et droit à chaque pas.

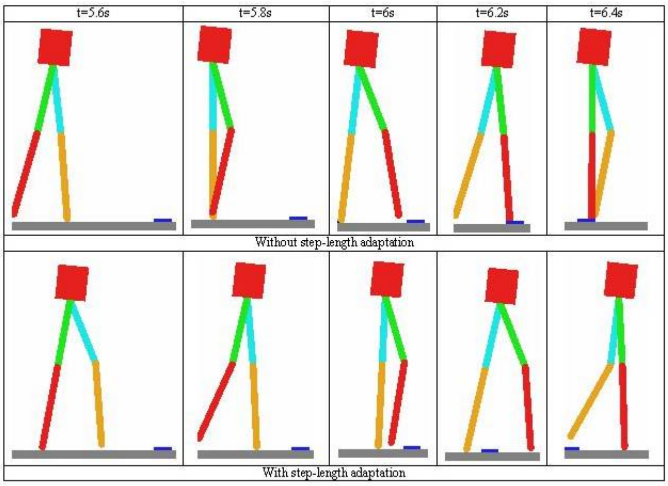

FIGURE 4.4.6: Résultat obtenu en simulation dans le cas d'un évitement d'un obstacle dynamique. Le SIF utilisé est celui défini par le tableau 4.2.

pectives intéressantes serait aussi d'utiliser la solution proposée au contrôle d'un exosquelette.

Chapitre 5

Perception et conceptualisation de connaissances

5.1 Introduction

Contrairement aux robots, l'Homme a la capacité, tout au long de sa vie, d'apprendre de nouvelles connaissances, de s'adapter à des environnements, des situations et des cultures très différentes. La part de l'acquis joue donc un rôle fondamental chez l'être humain. L'Homme est par exemple capable, en observant et en interagissant avec son environnement, de créer et d'imaginer de nouveaux concepts notamment en créant des relations entre des attributs perceptuels et des éléments du langage naturel [Poulin-Dubois 07]. Cette conceptualisation implique des facultés de généralisation et de déduction qui vont bien au-delà de la simple association entre une représentation visuelle d'un objet et un symbole linguistique extrait du langage naturel. Il est donc fondamental de repenser le « cerveau » des robots afin que l'assimilation de connaissances, comme pour les êtres humains, devienne prépondérante. Pour ce faire, les roboticiens doivent doter les robots de capacités d'apprentissages leur permettant, tout au long de leur utilisation, d'acquérir et de conceptualiser de nouvelles connaissances. Mais comme pour les êtres humains, l'acquisition de ces nouveaux savoirs doit se faire sur la base d'observations, chaque observation regroupant les informations perceptuelles associées aux éléments du langage naturel permettant de les décrire. La perception, ainsi que l'interaction homme-robot, sont par conséquent deux éléments fondamentaux au bon déroulement de ce processus d'acquisition et de conceptualisation de connaissances. Mais étant donné la multitude des données sensorielles brutes récupérées à chaque instant, il est aussi nécessaire de faire un prétraitement de l'ensemble des données perçues de manière à extraire seulement les informations sensorielles

les plus pertinentes, ainsi que les éventuels éléments du langage naturel qui leurs sont associés. Un autre aspect, aussi très important, est de comprendre la où les sources de motivation intrinsèque, de curiosité, qui stimulent cette acquisition de nouvelles connaissances chez l'être humain [Loewenstein 94]. La curiosité peut se définir comme un fort désir de connaître ou d'apprendre quelque chose [1]. Il est donc important de comprendre et de modéliser les sources de la curiosité afin de s'en inspirer pour concevoir des robots autonomes dont les connaissances évoluent constamment. Les modèles de la curiosité généralement proposés en psychologie postulent que les valeurs des stimuli générés lors d'une exploration sont caractérisées par une relation (incompatibilité, divergence, incertitude, ou au contraire, prévisibilité) entre un modèle prédictif interne et la structure réelle des stimuli [Kaplan 07].

Les travaux présentés dans ce chapitre s'inscrivent dans le développement d'un système cognitif artificiel permettant à un robot d'acquérir et de conceptualiser progressivement de nouvelles connaissances. Comme pour le cas de l'acquisition d'aptitudes motrices (chapitre 4), nous avons choisi de développer un système cognitif artificiel qui regroupe des processus cognitifs inconscients et des processus cognitifs conscients. Les PCI rassemblent l'ensemble des fonctions cognitives liées à la perception, et les PCC regroupent les fonctions cognitives associées à la conceptualisation de connaissances. L'originalité de notre solution est que ce système cognitif artificiel s'appuie notamment sur des fonctions cognitives modélisant la curiosité pour stimuler la collecte d'observations. En favorisant la collecte d'informations, ce système de curiosité artificielle contribue aussi à l'amélioration des interactions homme-machine car le robot peut décider d'interagir avec l'homme afin d'acquérir de nouvelles connaissances. La synthèse des travaux qui sont présentés ici n'a donc pas pour ambition de présenter un système cognitif doté de capacités de raisonnement permettant à un robot de solutionner des problèmes complexes. Mais il a pour objectif de décrire un système cognitif permettant à un robot de construire progressivement une représentation, une interprétation, du monde qui l'entoure à l'aide, premièrement, des moyens perceptifs qu'il a à sa disposition, et deuxièmement, grâce à sa capacité d'interaction avec d'autres agents réels (des êtres humains) ou bien artificiels (des robots).

Avant d'aborder la description détaillée de ces travaux, la section 5.2 sera destinée à présenter brièvement le contexte scientifique de ce travail. La première partie de cette section donnera un aperçu des fondements bio-inspirés qui reposent sur des études réalisées en psychologie cognitive. En effet, la psychologie cognitive

1. La définition donnée dans Oxford dictionary est « A strong desire to know or learn something »

étudie les grandes fonctions psychologiques de l'être humain comme le langage, le raisonnement, la perception, la mémoire, etc... Les résultats obtenus en psychologie cognitive, notamment sur le développement cognitif chez l'enfant, sont donc des sources d'inspiration importantes pour la conceptualisation de connaissance en robotique. La deuxième partie de la section 5.2 sera l'objet d'une brève présentation de l'état de l'art sur l'acquisition de connaissance et la construction de concepts en robotique. Les sections 5.3 et 5.4 seront consacrées respectivement à la description de notre système cognitif artificiel et la présentation des principaux résultats obtenus. Les travaux présentés dans la suite de cette section ont fait l'objet des thèses de Dominik M. RAMIK [Ramík 12] et de Jingyu WANG [Wang 15b] et ont été notamment publiés dans [Ramík 13b] [Ramík 14a] [Wang 15a] .

5.2 Contexte scientifique

5.2.1 Sources d'inspiration : la psychologie cognitive

Dès la naissance, un enfant possède déjà un répertoire de compétences rudimentaires qui vont lui permettre d'acquérir progressivement des connaissances nouvelles en relation avec son environnement. Ces connaissances serviront par la suite de socle pour les développements ultérieurs. Ainsi, dès les premiers mois de sa vie, un enfant a des capacités innées qui lui permettent d'identifier et de traiter les sons de la parole. Il va aussi prendre conscience de la permanence des objets (3 mois) et de l'identité des objets (4 mois) qui l'entourent. Les enfants peuvent très vite se représenter certaines propriétés des objets, et dès 1 an, ils sont capables de traiter les objets comme des entités distinctes sur la base des propriétés perceptives. Une autre aptitude fondamentale chez le très jeune enfant (avant 2 ans) consiste à pouvoir regrouper ou classer les propriétés, les objets ou les événements [Poulin-Dubois 07]. Ce processus de catégorisation qui permet le regroupement d'entités discriminantes sur la base de certaines règles réduit la diversité et la complexité du monde réel qui est perçue par les voies sensorielles. A titre d'exemple, bien que l'œil humain soit théoriquement capable de discriminer plusieurs millions de couleurs, l'homme utilise moins d'une vingtaine de mots pour les classer. Il est aussi important de noter que cette classification est dépendante de la langue et de la culture. En effet, comme cela a déjà été montré dans [Xu 02] [Plunkett 08], des éléments de langages simples facilitent les processus de catégorisation des objets, mais aussi des concepts comme les formes ou les couleurs. Par exemple, alors que généralement la plupart des populations notamment occidentales utilisent une dizaine de termes pour classer les couleurs, il n'en existe que 5 dans le langage Berinmo [Kay 07]. Ils ne distinguent notamment pas le bleu du vert. La perception spatiale et notamment le codage permettant de situer les objets dans l'espace peuvent aussi être influencés par le langage [Majid 04]. On peut donc supposer que chez l'homme, cette association entre perception et langage naturel permet d'enclencher des processus de catégorisation. En donnant du sens à ce que l'on perçoit, ces éléments de langage permettent aussi à l'être humain de partager sa connaissance. Par ailleurs, certains scientifiques émettent aussi l'idée que le langage naturel a émergé du grand nombre de catégories et de concepts que l'homme a formé [Reboul 07], et que par conséquent, le langage est avant tout un outil cognitif permettant aux êtres humains d'acquérir des connaissances. Le langage joue donc un rôle fondamental dans l'interprétation de la perception et l'acquisition de connaissances. Partant de ce constat, l'acquisition et la conceptualisation de connaissances en intelligence artificielle, et plus particulièrement en robotique, doit se fonder sur des processus d'apprentissage intégrant, d'une part, la perception, et d'autre part, l'interaction verbale entre le robot et un homme, comme pourrait le faire un jeune enfant en interagissant avec ses parents.

La curiosité est aussi un point fondamental pour l'acquisition de connaissances. Mais le problème est alors de définir ce qui caractérise exactement la curiosité. Dans "Theory of human curiosity" [Berlyne 54], Berlyne propose de diviser cette curiosité en deux catégories distinctes qui sont la curiosité perceptuelle et la curiosité épistémique. La curiosité perceptuelle permet de sélectionner, de manière inconsciente, les informations importantes qui sont perçues par les voies sensorielles. La curiosité perceptuelle et l'« attention » sont donc deux processus cognitifs intimement liés, voire identiques. Car bien qu'en psychologie cognitive, l'attention soit un phénomène complexe difficile à définir car elle recouvre des domaines très vastes, une des définitions communément admise est « la capacité de sélectionner une information pertinente au milieu d'un flux d'informations différentes » [Chanquoy 07]. L'attention est donc un processus cognitif qui permet à un être humain de se focaliser sur une partie ou un aspect des informations qu'il perçoit en ignorant les autres. La nature de l'attention peut être soit ascendante (bottom-up), soit descendante (top-down). La curiosité épistémique, quant à elle, correspond au désir d'apprendre de nouvelles connaissances, de résoudre des problèmes [Litman 08]. Cette curiosité épistémique est aussi liée à la mémorisation à long terme [Kang 09]. Par conséquent, la solution proposée par Berlyne a pour avantage de décomposer la curiosité en deux fonctions cognitives distinctes qui sont la curiosité perceptuelle, assimilable à un PCI, et la curiosité épistémique assimilable à un PCC. Dans ce cas, la curiosité perceptuelle qui correspond à un processus inconscient (bottom-up) permet d'initier et de stimuler des comportements d'exploration. Les modèles computationnels utilisés pour modéliser l'attention peuvent alors servir de base pour élaborer des modèles de curiosité perceptuelle artificielle comme c'est le cas pour l'attention visuelle (visual saliency) ou l'attention auditive. La curiosité épistémique, quant à elle, modélise des comportements conscients (top-down) permettant de diriger l'exploration pour acquérir ou renforcer la fiabilité de nouvelles connaissances.

5.2.2 Robotique autonome et acquisition de connaissances

Pendant très longtemps, la connaissance (le savoir) d'un robot se limitait à ce que les ingénieurs lui implantaient lors de sa conception. Puis progressivement, les robots ont été capables d'acquérir de nouvelles connaissances notamment grâce à l'amélioration des techniques de perception et l'utilisation d'algorithmes d'apprentissage. Aujourd'hui, une des principales fonctions dont sont dotés les robots autonomes est la reconnaissance d'objets ou de lieux (de scènes) afin de leurs associer des attributs. Ce type de problématique, plus communément connu sous le terme anglais « anchoring » [2] [Coradeschi 03], consiste à associer, pour chaque objet physique distinct, des informations sémantiques et des données perçues permettant de caractériser cet objet. Cette acquisition de connaissances peut s'effectuer via une interaction homme-robot [Randelli 13] [Holzapfel 08] [Nakamura 12], ou bien par la collecte d'informations sur internet [Daoutis 12]. Cependant, dans les études évoquées précédemment, on se contente d'associer des attributs comme des couleurs, des formes, à des objets distincts. En résumé, le robot apprend que tel objet est rouge ou bleu, mais il n'a pas appris à reconnaître les couleurs rouge ou bleu. Il n'y a donc pas de possibilité de généralisation. Cependant, dans [D'Este 08], les auteurs utilisent un programme basé sur la logique inductive pour tenter de généraliser des relations entre des objets et leurs attributs. Et dans [De Greeff 09], les auteurs décrivent une méthode où deux agents virtuels, dont l'un se comporte comme un enseignant et l'autre comme un apprenant (langage game), interagissent réciproquement afin que l'apprenant arrive à créer de nouveaux concepts (catégories).

Quant à la curiosité artificielle, elle a aussi fait l'objet de certains travaux en robotique (voir par exemple [Oudeyer 07]). Une partie de ces travaux s'est focalisée sur l'exploration sensori-motrice du robot, le but étant que le robot découvre par lui-même sa capacité à interagir physiquement avec son environnement. Certains travaux se sont aussi orientés sur la création de robots attentifs en utilisant essentiellement l'attention visuelle de manière ascendante, pour l'exploration sans but précis, ou descendante dans le cas de la recherche d'un objectif précis [Frintrop 11]. Une des premières études majeures concernant la modélisation de l'attention visuelle a été proposée par C. Koch et S. Ullman [Koch 85]. L'attention visuelle est

2. La définition exacte du terme « anchoring » donnée par S. Coradeschi et A. Saffiotti est : « anchoring is the problem of connecting, inside an artificial system, symbols and sensor data that refer to the same physical objects in the external world ».

généralement représentée sous la forme d'une cartographie spatiale (image en niveau de gris) mettant en évidence les parties qui semblent les plus « pertinentes » dans une image. Cette cartographie de l'attention visuelle est obtenue en fusionnant les résultats de filtrage liés à différents attributs de l'image comme la couleur ou l'orientation de manière à faire apparaître des contrastes. Par exemple, un ballon de couleur rouge posé sur une pelouse verte attirera certainement plus l'attention que celle d'un ballon vert. Il existe aujourd'hui de nombreux modèles computationnels ([Borji 13]) et la validité de ces modèles est souvent évaluée en comparant les résultats obtenus avec une référence expérimentale représentant une carte statistique des points de fixation de différents observateurs [3]. A noter qu'il existe aussi des modèles pour l'attention auditive. Dans ce cas, le signal sonore est généralement converti sous la forme d'une représentation temps fréquences (spectrogramme), ce qui permet d'utiliser des techniques similaires à celles employées pour l'attention visuelle [Kayser 05] [Kalinli 07] [Kaya 12].

Malgré les efforts réalisés par la communauté scientifique, force est de constater que encore aujourd'hui, les robots sont loin d'égaler les performances des êtres humains dans les processus d'acquisition, et plus particulièrement, de conceptualisation autonome de connaissances.

5.3 Système cognitif artificiel dédié à la conceptualisation de connaissances

Comme je l'ai évoqué précédemment, un robot compagnon doit pouvoir s'adapter à des environnements, des configurations qui évoluent continuellement. Un robot compagnon doit donc être capable d'acquérir et de conceptualiser, progressivement, des nouvelles connaissances sur la base de ses propres expériences (observations). Ces expériences, qui résultent d'une interaction verbale homme-robot, permettent l'acquisition et l'association d'informations sensorielles (visuelles, auditives, etc..) avec des éléments du langage naturel. L'acquisition de connaissances peut être déclenchée par une curiosité perceptuelle (motivation intrinsèque inconsciente) ou bien motivée par une curiosité épistémique (motivation intellectuelle) permettant de satisfaire un désir d'acquérir de nouveaux savoirs. Cependant, si perception et curiosité jouent des rôles importants dans l'acquisition de connaissance, elles ne sont pas suffisantes pour conceptualiser des connaissances. Car la création de nouveaux concepts découle d'une capacité de généralisation qui doit permettre, à terme, d'interpréter chaque observation. Ce processus de conceptualisation nécessite donc une phase d'apprentissage afin de définir des « croyances »

3. voir par exemple http ://saliency.mit.edu/

qui représenteront les relations entre les données perceptuelles et le langage naturel.

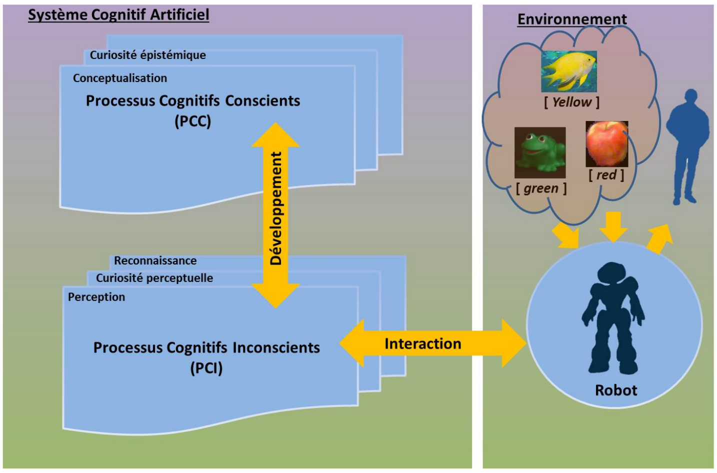

FIGURE 5.3.1: Illustration fonctionnelle du système cognitif artificiel appliqué à la perception et conceptualisation de connaissances. Une partie du SCA regroupe les PCI qui concernent la perception et l'autre les PCC pour la conceptualisation de connaissances.

La figure 5.3.1 schématise la structure du système cognitif artificiel destiné à réaliser cette conceptualisation de connaissances. Les PCI permettent d'extraire, à partir des observations, les informations pertinentes ainsi que les éléments du langage naturel [4]. Le deuxième niveau, qui regroupe quant à lui les PCC, a pour objectif de créer des concepts sur la bases de l'élaboration de croyances en utilisant des algorithmes d'apprentissages (algorithme génétique dans notre cas). La section 5.3.1 fera l'objet de la description des processus cognitifs inconscients qui regroupent l'ensemble des fonctions liées à la perception et la section 5.3.2 sera consacrée à la présentation des processus cognitifs conscients relatifs à la création de concepts.

5.3.1 Processus cognitifs inconscients

Bien que nos travaux se soient essentiellement focalisés sur la perception visuelle, nous avons aussi étendu certains de nos travaux à la perception auditive. Je commencerai donc cette section en présentant les résultats obtenus sur l'attention

4. Dans la suite de ce chapitre, nous nous focaliserons sur l'extraction des attributs visuels, la reconnaissance et l'identification des mots prononcés par le tuteur ne faisant pas partie du travail présenté ici.

visuelle [Ramík 14a] et je poursuivrai en abordant brièvement les résultats obtenus pour l'attention auditive [Wang 15a].

5.3.1.1 Attention visuelle

Le système que nous avons proposé, schématisé sur la 5.3.2, est constitué de plusieurs unités collaborant ensemble pour accomplir simultanément la détection de nouveaux « objets » [5] saillants via l'utilisation de l'attention visuelle ainsi que l'identification directe des objets déjà connus via des algorithmes de reconnaissance existants comme SURF [Bay 08] ou SIFT [Lowe 99]. Le rôle du module dédié à l'attention visuelle est donc de détecter les zones d'intérêt nouvelles afin d'extraire des segments [6] d'images pour alimenter la base de données nécessaire aux algorithmes de reconnaissance d'objets. Et, étant donné que notre système capture des images successives à intervalle de temps constant, cette base de données est alimentée continuellement par des segments qui sont automatiquement classés comme nous le verrons ultérieurement. Les différentes classes de la base de données, constituées par des groupes de segments, sont ensuite utilisées pour identifier directement les objets qui ont été préalablement appris. Et bien que notre système perceptif ne soit pas réellement dépendant du codage des couleurs de l'image, il est toutefois important de souligner que nous avons choisi d'utiliser la modélisation siRGB [Ramík 14a]. Cette solution qui différencie la chromacité et la luminance nous a notamment permis de gagner en robustesse en limitant les effets néfastes liés aux conditions d'illumination (ombres, reflets lumineux, etc).

Afin de détecter les objets saillants dans le champ visuel du robot, nous avons proposé une nouvelle approche du calcul de la cartographie de la saillance visuelle. Le calcul de cette cartographie repose sur la fusion d'une carte de saillance globale $M(x)$ avec une carte de saillance locale $D(x)$. $M(x)$ est déterminée en fusionnant les cartes de saillance de l'intensité $M_l(x)$ et la carte de saillance de la chromacité $M_{\phi\theta}(x)$. La fusion de ces deux cartes se fait via l'utilisation d'une fonction sigmoïde qui permet, suivant les paramètres RGB de chaque pixel, de donner plus ou moins d'importance à la partie chromacité ou intensité. $D(x)$, comme pour la saillance globale, est calculée en fusionnant les composantes liées à la luminance et la chromacité. La figure 5.3.3 résume ce processus de calcul. Il est important de rappeler que l'objectif du calcul de la cartographie de la saillance n'est pas de déterminer avec exactitude le contour d'un objet mais plutôt de localiser, dans une image, la ou les portions d'image qui semblent être les plus intéressantes et qui

5. Le terme « objets » fait ici seulement référence à la perception visuelle 2D de celui-ci.

6. Les segments sont obtenus après un traitement d'images (segmentation de l'image) qui a pour but de classer, à partir de critères prédéfinis, des pixels dans des groupes. Dans notre cas, un segment représente un ensemble de pixels censés appartenir à un même objet.

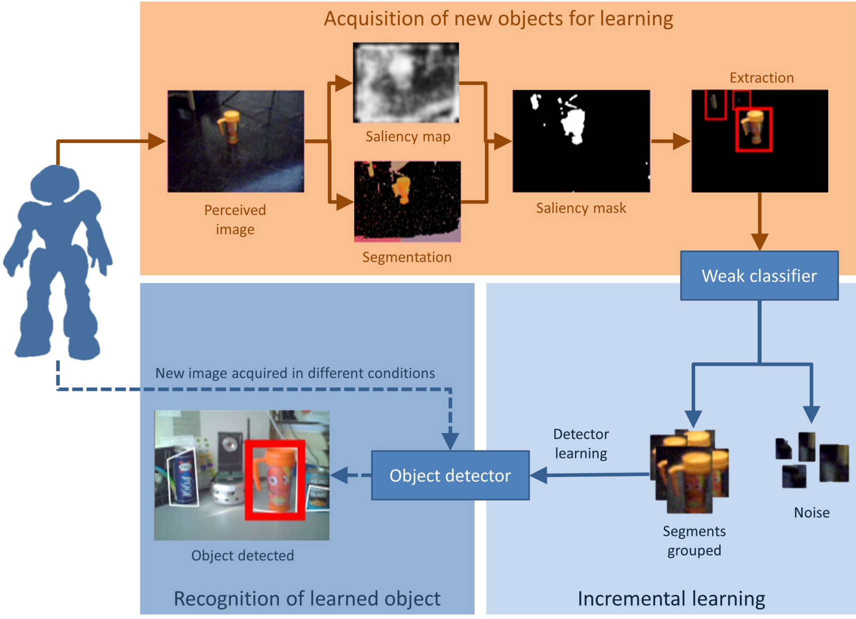

FIGURE 5.3.2: La partie du système de perception visuelle identifiée comme "Acquisition of new objects for learning" assure la détection des objets pertinents ainsi que l'extraction des segments qui lui sont associés, via le calcul en parallèle d'une carte de saillance et d'un algorithme de segmentation. La deuxième partie repose sur l'utilisation d'algorithmes de reconnaissance comme SURF ou SIFT.

sont supposées représenter des objets saillants. Cette cartographie de la saillance, représentative de l'attention visuelle, est associée à des algorithmes de segmentation afin d'extraire les segments appartenant seulement aux objets pertinents. Le problème consiste maintenant à déterminer la correspondance entre segments et objets (classification) afin d'alimenter la base de données qui servira ultérieurement à la reconnaissance de ces même objets.

L'algorithme 1 décrit la méthode utilisée pour classer chaque segment dans les différents groupes qui sont supposés représenter des objets pertinents. Il est important de noter que cet algorithme permet de créer automatiquement les groupes, cependant seul ne sont conservés que les groupes ayant un nombre d'échantillons significatifs. Et afin de diminuer les temps de calcul pour une utilisation en « temps réel », nous avons utilisé une combinaison de quatre classificateurs $\{w_1, w_2, w_3, w_4\}$, chacun de ces classificateurs renvoyant simplement une information binaire, permettant d'indiquer si le segment est supposé appartenir ou ne pas appartenir à un groupe. Les quatre classificateurs w_1, w_2, w_3, w_4 permettent de comparer les seg-

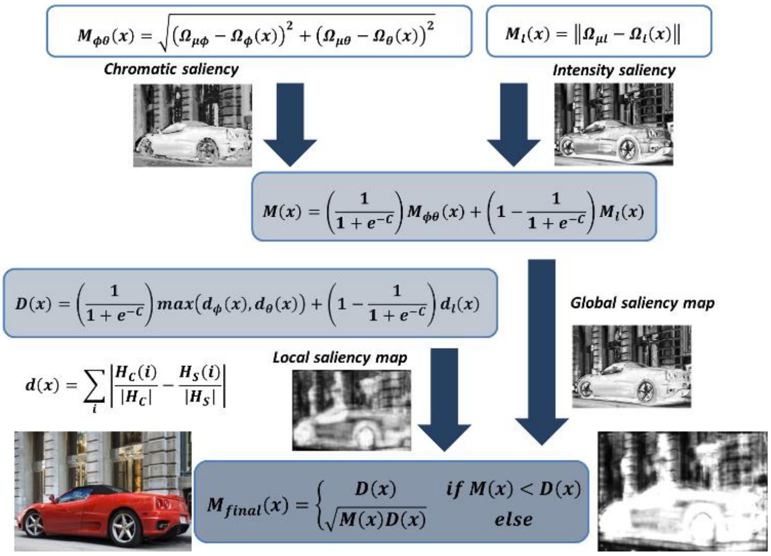

FIGURE 5.3.3: La carte de la saillance résulte de la fusion d'une carte de saillance globale $M(x)$ avec une carte de saillance locale $D(x)$. $M(x)$ et $D(x)$ sont calculés en fusionnant les composantes liées à la luminance et la chromacité.

Algorithm 1 On-line object learning

```
acquire image
extract fragments by salient object detector
for each fragment F
    if(F is classified into one group)
        populate the group by F
    if(F is classified into multiple groups)
        populate by F the closest group by Euclidean distance of features
        if(F is not classified to any group)
            create a new group and place F inside
select the most populated group G
    use fragments from G as learning samples for object detection algorithm
```

ments par rapport respectivement à leurs tailles, leurs aspects, leurs chromacités et l'uniformité de leurs textures. Un segment appartient à un groupe si et seulement si $\prod_{i=1}^{4} w_i = 1$. Une classe ne peut accumuler qu'un seul segment par image à un instant t, et dans le cas ou un segment est supposé appartenir à plusieurs classes, le segment est assigné à la classe dont il est le plus proche au sens de la distance euclidienne. Cette base de données, constituée de groupes de segments, est ensuite utilisée par des algorithmes de reconnaissances (SURF, SIFT). La figure 5.3.4 illustre quelques exemples de reconnaissance d'objet dans des conditions réelles. Le taux de réussite de la reconnaissance est de l'ordre de 90% dans le cas de l'utilisation de l'algorithme SURF.

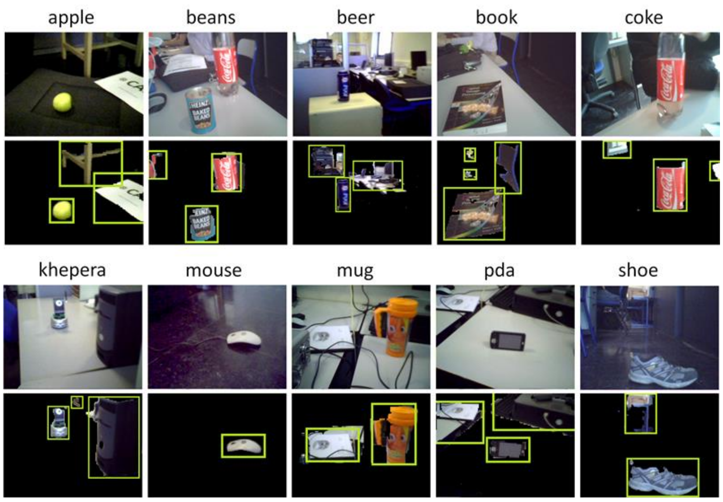

FIGURE 5.3.4: Exemple de résultats illustrant la reconnaissance d'objets (entourés d'un rectangle jaune) dans des conditions réelles. Le taux de réussite de la reconnaissance est de 90% dans le cas de l'utilisation de SURF.

5.3.1.2 Attention auditive

Fort de ces résultats, nous avons étendu notre étude au calcul d'une cartographie de la saillance auditive. Toujours sur des bases bio-inspirées, nous avons proposé une nouvelle méthode de saillance auditive permettant d'isoler et de reconnaître des sons ou des bruits environnementaux comme le klaxon d'une voiture ou bien la sirène d'une voiture de police. La détection de ces sons saillants repose sur la prise en compte d'un ensemble de caractéristiques hétérogènes. La figure 5.3.5 synthétise l'ensemble du calcul de cette carte de saillance auditive. Concrètement, la saillance de l'information sonore est déterminée en fusionnant les données extraites des représentations temporelles et spectrales du signal acoustique avec une

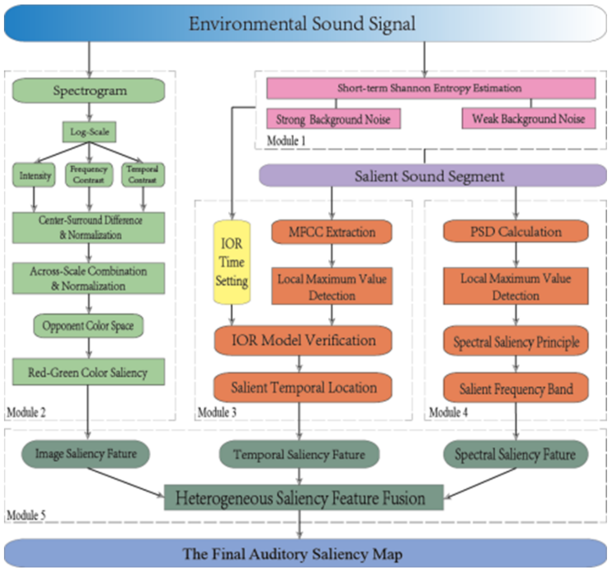

FIGURE 5.3.5: La saillance de l'information sonore est déterminée en fusionnant les données extraites des représentations temporelles et spectrales du signal acoustique avec une carte de saillance du spectrogramme du signal analysé.

carte de saillance visuelle du spectrogramme du signal analysé. Les caractéristiques représentatives de la saillance, des points de vue temporel et fréquentiel, sont déterminées à partir des coefficients MFCC (Mel Frequency Cepstrum Coefficient) et du calcul de la densité spectrale de puissance (Power Spectral Density).

Les résultats expérimentaux ont prouvé l'intérêt de cette solution notamment lorsque le bruit de fond est important ou lorsqu'il y a plusieurs sons saillants. La figure 5.3.6 illustre les résultats obtenus sur deux exemples différents. Dans le premier cas (a), le signal sonore concerne l'enregistrement d'une sirène de police ainsi qu'un événement sonore court de type klaxon. Dans le deuxième cas (b), le signal sonore correspond à un enregistrement de bruits de sabots que font les chevaux en marchant. Des bruits de fond sont inclus dans les deux exemples mais ils sont d'un niveau sonore plus important dans le cas de l'exemple b. Les résultats obtenus montrent bien que dans les deux cas, les sons saillants sont clairement mis en évidence par la carte de saillance auditive.

5.3.2 Processus cognitifs conscients

La création de concepts passe obligatoirement par la collecte d'un ensemble d'observations $O = \{o_1, o_2, ..., o_k\}$. Chaque observation $o_k = \{I, U\}$ est définie

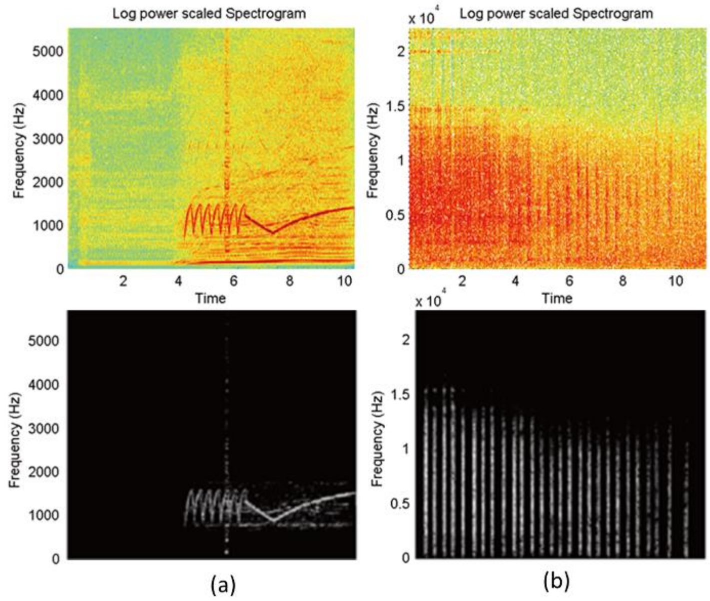

FIGURE 5.3.6: Illustration des résultats obtenus dans le cas du calcul de la saillance auditive.

comme une association d'informations sensorielles (features) $I = \{i_1, i_2, ..., i_j\}$ et de termes linguistiques (utterances) $U = \{u_1, u_2, .., u_i\}$. Il est important de souligner que nous considérons ici la capacité de la perception des termes linguistiques comme une habilité à part entière et que notre système est capable de différencier les sons liés au langage des sons environnementaux. Bien que dans la suite de ce chapitre nous nous focaliserons sur des informations sensorielles visuelles, les informations perçues I pourraient provenir d'autres canaux sensoriels (auditifs, olfactifs, etc..). De plus, les résultats présentés dans la suite de ce chapitre s'appuieront exclusivement sur l'exemple de la conceptualisation des couleurs, mais l'approche que nous proposons peut s'inscrire dans un cadre de création de concepts plus généraux (couleurs, formes, positionnement dans l'espace, etc..). La figure 5.3.7 illustre la notion d'« observation » censée être faite par un robot. Supposons que ce robot puisse percevoir distinctement un poisson dans un aquarium et demande à un être humain de le décrire, l'observation $o_1 = \{i_1, i_2, i_3, ..., "jaune"\}$ faite par le robot correspondrait alors à un ensemble d'attributs visuels $I = \{i_1, i_2, ..., i_j\}$ (par exemple un ensemble de segments de couleurs différentes mais appartenant à la même entité : le poisson) et un mot du langage naturel $u_1 = \{"jaune"\}$. Le problème consiste alors à associer les informations sensorielles pertinentes i_p (les segments de couleurs jaunes) avec l'élément du langage naturel « jaune ». Dans ce contexte, la problématique est de pouvoir différencier les informations pertinentes

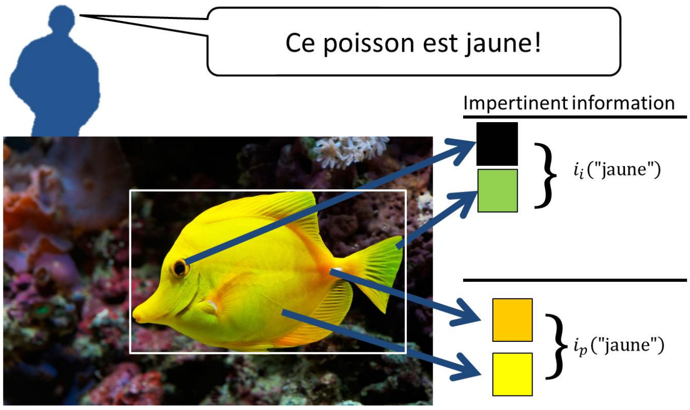

FIGURE 5.3.7: Illustration du concept d'une observation $o_1 = \{i_1, i_2, i_3, ..., "jaune"\}$ faite par un robot. Les informations sont décomposées en informations pertinentes (i_p) et informations non pertinentes (i_i). Le mot du langage naturel permettant de caractériser cette observation est $u_1 = \{"jaune"\}$.

i_p (la ou les nuances de jaune) des informations non pertinentes i_i afin de les associer à la catégorie qui est représentée par le mot prononcé par le tuteur. De cette interrogation découle bien sûr une évidence : une seule observation ne peut suffire à résoudre ce problème.

La figure 5.3.8 schématise le processus d'acquisition et d'interprétation des informations perçues lors de plusieurs observations ($o_1 = \{i_1, i_2, i_3, i_4, green\}, o_2 = \{i_5, i_6, white, red\}$, $o_3 = \{i_7, i_8, i_9, green, white\}$). Chaque observation correspond à un ensemble de données hétérogènes regroupant des informations ($i_1, i_2, i_3, i_4, etc..$) extraites des signaux sensoriels (couleurs dans notre cas) et des mots prononcés par un tuteur (« green », « white », « red »). Pour chaque observation, les informations sensorielles $I = \{i_1, i_2, ..., i_j\}$ représentant les couleurs de chaque segment sont déterminées via une segmentation de l'image et codées sous forme numérique (par exemple codage RGB). Le problème consiste maintenant à interpréter ces observations en associant les couleurs des différents segments, identifiés au moyen d'une segmentation de couleur (méthode K-means par exemple), à leur classe respective comme le schématise la figure 5.3.9. En définissant :

- $I = \bigcup i_p(u) + \bigcup i_i(u)$ comme l'ensemble des informations pertinentes i_p et des informations non pertinentes i_i,
- $X(u) = \{u, I_j \subseteq I\}$ une interprétation de u permettant d'associer à la catégorie u les perceptions adéquates (par exemple $(X(green) = \{green, i_1, i_7\})$),
- et $U_B = \{X(green), X(white), X(red)\}$ la croyance qui permet de déterminer

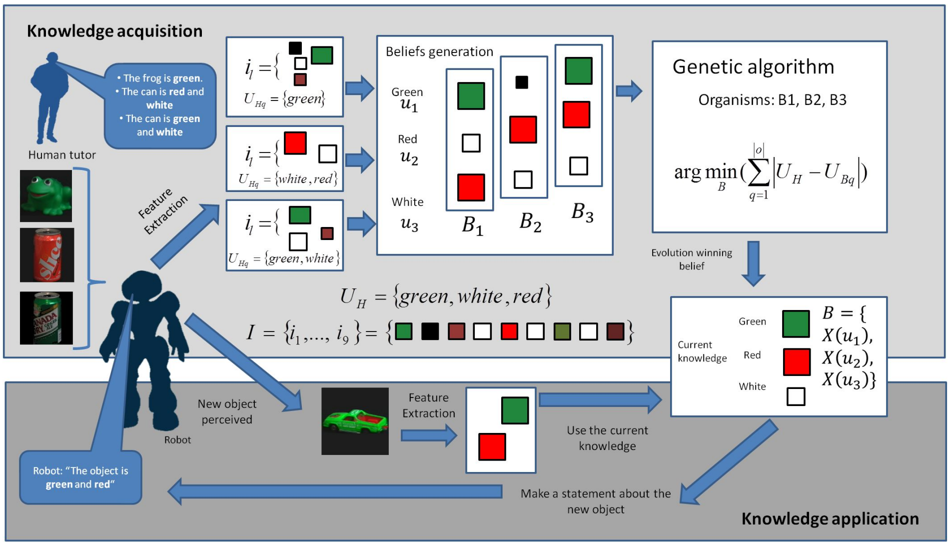

FIGURE 5.3.8: Le robot effectue une série d'observations : $o_1 = \{i_1, i_2, i_3, i_4, green\}$, $o_2 = \{i_5, i_6, white, red\}$ et $o_3 = \{i_7, i_8, i_9, green, white\}$. Après une phase d'apprentissage, le robot est capable de déduire que la voiture est rouge et verte.

l'ensemble des interprétations $X(u)$.
Alors il est possible de trouver la croyance U_B qui se rapproche le plus possible de la réalité via un processus d'optimisation comme celui défini par l'équation 5.3.1, où pour chaque observation $o_q \in O$, U_{Hq} représente les mots prononcés par le tuteur et U_{Bq} correspond aux interprétations générées par le robot.

$$\arg\min_B \left(\sum_{q=1}^{|O|} |U_{Hq} - U_{Bq}| \right) \tag{5.3.1}$$

La solution développée pour résoudre ce problème d'optimisation (5.3.1) repose sur l'utilisation d'un algorithme génétique, où chaque organisme correspond à une croyance (U_{Bq}), cette croyance représentant un ensemble d'interprétations $X(u)$. Le problème se résume alors, via un processus évolutif, à trouver la croyance U_B qui se rapproche le plus possible de la réalité U_H. Et avant d'expérimenter la solution décrite précédemment avec un robot réel, nous avons choisi de la valider par une première évaluation dans un environnement virtuel. Pour cela, nous avons utilisé la base de données de « Columbia Object Image Library Database » [Nayar 96] qui contient des images d'une centaine d'objets. Chacun de ces objets a été décrit à l'aide de une ou deux couleurs. Le choix des couleurs étant limité à : Noir, gris, blanc, rouge, vert, bleu et jaune. Les figures 5.3.10 et 5.3.11 illustrent les résultats

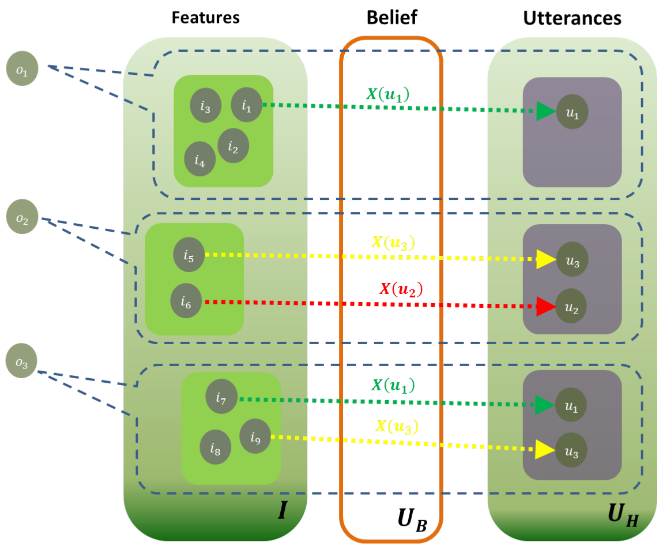

FIGURE 5.3.9: Interprétation des observations en associant les couleurs des différents segments : $X(u_1) = \{u_1, i_1, i_7\}$, $X(u_2) = \{u_2, i_6\}$, $X(u_3) = \{u_3, i_5, i_9\}$.

obtenus après l'utilisation de la méthode présentée dans cette section. La figure 5.3.10 représente une comparaison entre les couleurs comme définies dans « world color survey database » et la classification des couleurs après apprentissage. La figure 5.3.11, quant à elle, permet de montrer les couleurs, de quelques objets de cette base de données, telles qu'elles sont perçues par le système.

5.4 Principaux Résultats Expérimentaux

Après les tests effectués en simulation, nous avons réalisé différentes expérimentations à l'aide de la plate-forme robotique Nao. Afin de vérifier les capacités du robot à acquérir, mais aussi restituer, des concepts nouveaux, plusieurs scénarios ont été mis en œuvre. Dans la suite de cette section, je présenterai les résultats concernant la catégorisation des couleurs obtenue lors de ces expérimentations [Ramík 13a] et [Ramík 14b]. Cependant, avant d'exposer ces résultats, je commencerai par décrire brièvement l'architecture logicielle développée pour cette plate-forme robotique expérimentale.

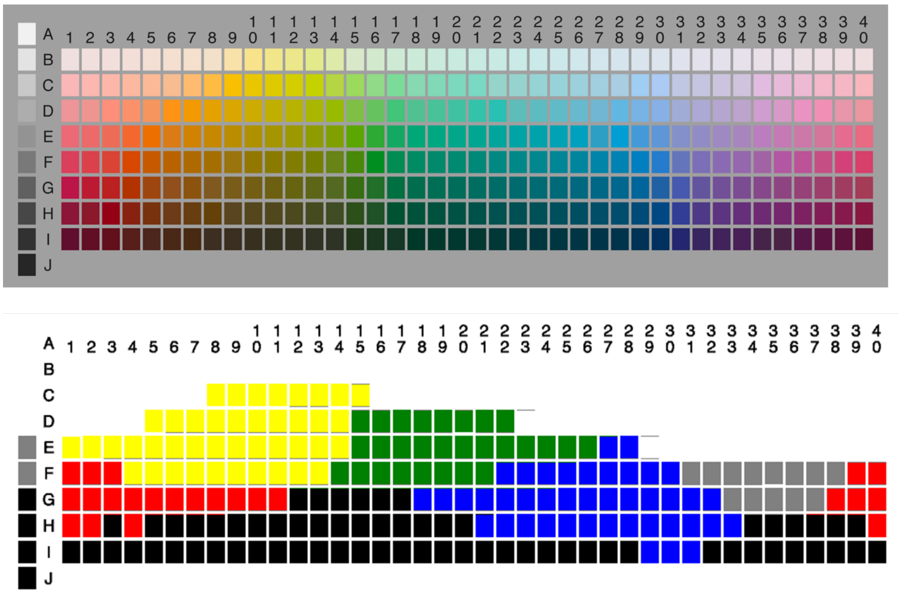

FIGURE 5.3.10: Représentation de la table des couleurs d'après « world color survey database » (haut de la figure), et représentation de la classification des couleurs après apprentissage (bas de la figure).

FIGURE 5.3.11: Comparaison des couleurs réelles des objets et celles perçues par le système après apprentissage.

5.4.1 Architecture matérielle et logicielle

Le robot Nao [7] est un robot humanoïde programmable de 58 cm équipé notamment de plusieurs caméras, microphones et haut-parleurs qui lui permettent de percevoir et communiquer avec son environnement. L'ensemble des programmes ont été codés en c# et exécutés sur un ordinateur distant, l'objectif ici n'étant pas d'embarquer les programmes sur le robot mais de le contrôler à distance afin de valider nos résultats. La figure 5.4.1 schématise l'architecture logicielle qui peut être décomposée en 5 unités qui sont :

- L'unité de communication pour gérer l'interaction homme-robot.
- L'unité de navigation du robot pour le positionner et le diriger dans son environnement.
- L'unité de perception (The Low-level Knowledge Acquisition Unit) pour collecter les informations sensorielles.
- L'unité d'acquisition de connaissances (High-level Knowledge Acquisition Unit) pour créer de nouveaux concepts.
- L'unité de contrôle pour coordonner l'ensemble des autres unités.

La figure 5.4.2 représente plus spécifiquement le principe d'interaction homme-robot. La détection des objets est notamment améliorée via la détection de la main du tuteur. Concernant l'interaction vocale homme-robot, nous avons utilisé l'outil de reconnaissance vocale du robot ainsi que le logiciel « TreeTagger » [8] afin de déterminer les informations données par le tuteur. L'association de ces deux outils permet d'extraire les informations sémantiques du message vocal du tuteur. Pour l'interaction vocale robot-homme, nous avons utilisé l'outil « text-to-speech » fourni avec le robot Nao.

5.4.2 Résultats

Dans le cadre de ces expérimentations, 25 objets de la vie courante ont été rassemblés (voir figure 5.4.3). Dans un premier temps, le tuteur a présenté les objets un par un au robot. Lors de chaque observation, le tuteur nommait explicitement l'objet. Ce prérequis est indispensable pour que le robot puisse par la suite identifier et nommer les objets. Dans un deuxième temps, l'ensemble des objets a été divisé en deux groupes, le premier étant destiné à la phase d'apprentissage et le deuxième à la phase de validation. Lors de la phase d'apprentissage, le tuteur a présenté au robot les objets en les décrivant (par exemple « le livre est noir » ou « le livre est blanc et rouge »). Le robot, après identification de l'objet, pouvait alors extraire les couleurs de l'objet désigné. Suite à cette phase d'apprentissage qui a permis au robot de conceptualiser les couleurs grâce à un ensemble d'observations, nous avons

7. http ://www.aldebaran.com/fr
8. http ://www.ims.uni-stuttgart.de/ projekte/corplex/TreeTagger/

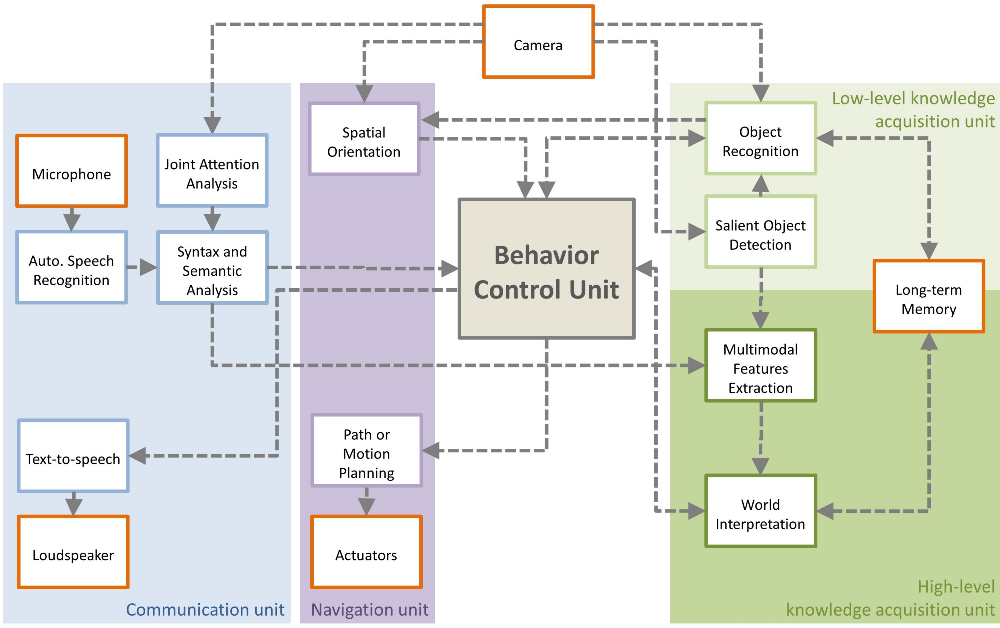

FIGURE 5.4.1: Description de l'architecture logicielle et matérielle de la plateforme robotique expérimentale ayant pour support principal le robot humanoïde Nao.

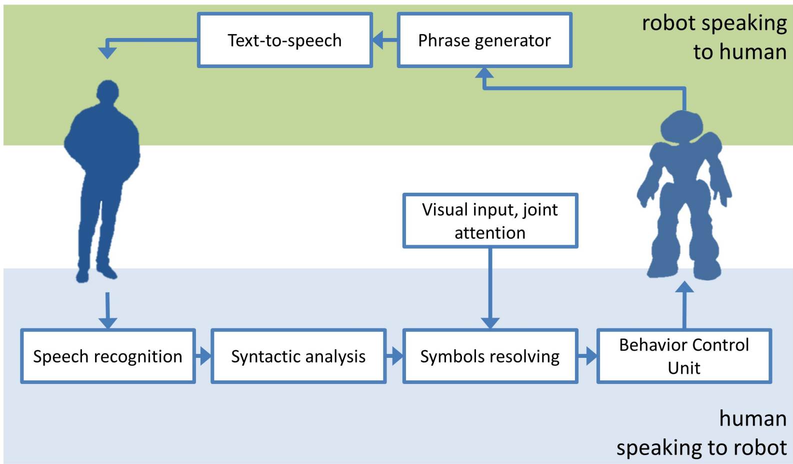

FIGURE 5.4.2: Schéma descriptif des interactions verbales entre le tuteur et le robot.

vérifié cette acquisition de nouveaux concepts en utilisant les objets du deuxième

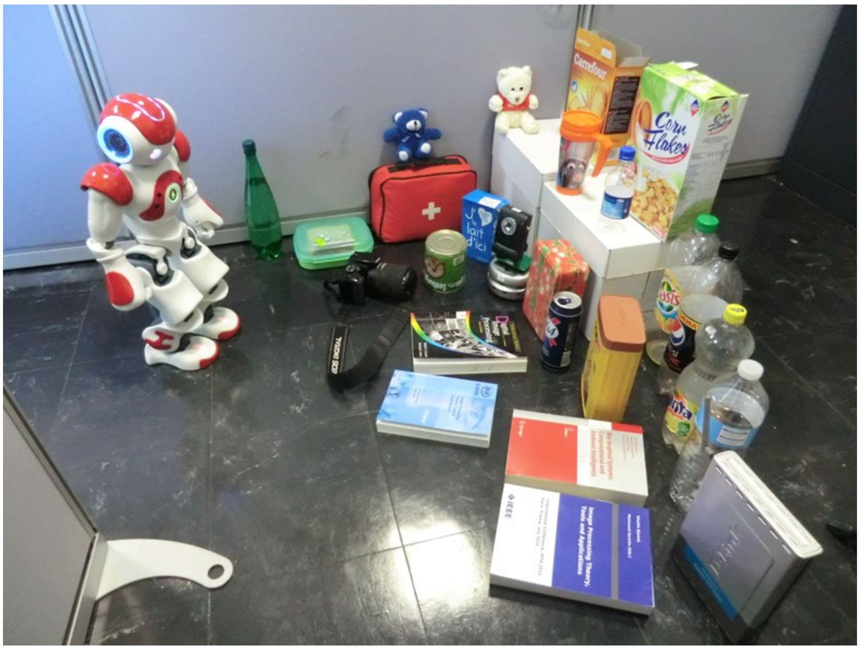

FIGURE 5.4.3: Le robot Nao devant un échantillon d'objets de la vie courante utilisées lors des validations expérimentales.

groupe. Lors de cette deuxième phase, le tuteur a demandé au robot de nommer et de décrire des objets. La figure 5.4.4 illustre quelques résultats des expériences qui viennent d'être décrites. Sur la figure 5.4.4 (a) et (b), le tuteur attire l'attention du robot sur un objet et lui demande de le décrire. Le robot répond alors au tuteur que la boîte est jaune. La figure 5.4.4 (c) illustre quant à elle la perception des couleurs du robot pour un objet particulier, une pomme rouge dans le cas présent.

La dernière expérience, illustrer par la figure 5.4.5, permet de démontrer les capacités du robot à utiliser la notion de concept pour initier des comportements « intelligents ». Dans cette expérience, le tuteur commence par demander au robot de se diriger vers un livre. Après observation, le robot découvre trois objets qu'il assimile à des livres, il demande alors au tuteur plus de précisions. Le tuteur lui indique de se diriger vers le livre rouge. Après analyse des différentes couleurs des livres, le robot se dirige vers le livre rouge.

5.5 Conclusion

Dans ce chapitre, j'ai présenté un système cognitif artificiel qui permet à un robot de créer progressivement de nouveaux concepts. Ce système est constitué de processus cognitifs inconscients modélisant la partie perception et de processus

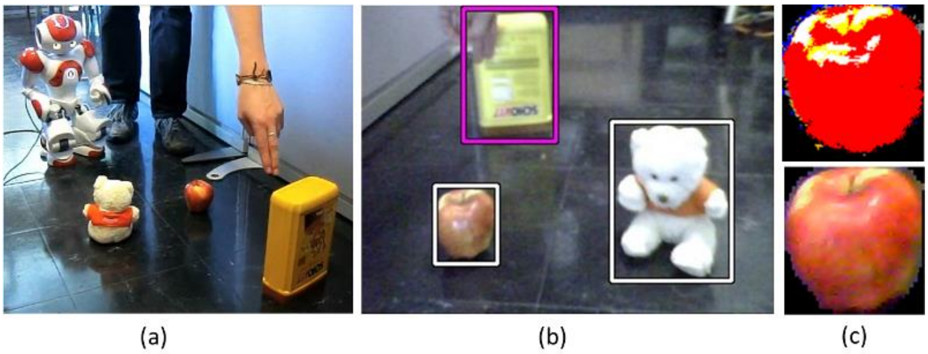

FIGURE 5.4.4: Exemple d'expérience où le tuteur demande au robot de lui décrire l'objet pointé du doigt. Le robot répond alors au tuteur que cet objet est jaune. Illustration de la perception des couleurs de deux objets par le robot.

cognitifs conscients modélisant la partie conceptualisation. Une des originalités de ce travail est qu'il s'appuie aussi sur des fonctions cognitives permettant de modéliser les effets de la curiosité. La curiosité stimule la collecte d'informations via des observations et elle contribue aussi à l'amélioration des interactions homme-machine car le robot peut décider d'interagir avec son tuteur afin d'acquérir de nouvelles connaissances. L'ensemble de la solution proposée a été validé expérimentalement pour le cas de la conceptualisation de couleurs, premièrement dans un environnement purement virtuel, et deuxièmement, dans un environnement réel à l'aide du robot Nao.

Ces premiers résultats, très prometteurs, permettent d'envisager de nombreuses perspectives à moyen terme. La première consiste à étendre cette approche à des concepts autres que la couleur, comme les formes, les représentations spatiales ; en proposant des algorithmes de co-évolution permettant d'apprendre simultanément les formes et les couleurs. La deuxième consiste aussi à généraliser cette approche à d'autres sens (ouïe, odorat, toucher, etc..). Sur le long terme, l'objectif est bien sûr de concevoir un robot doté d'une très grande autonomie en ce qui concerne l'acquisition et la conceptualisation de connaissances pouvant répondre aux exigences d'un robot compagnon.

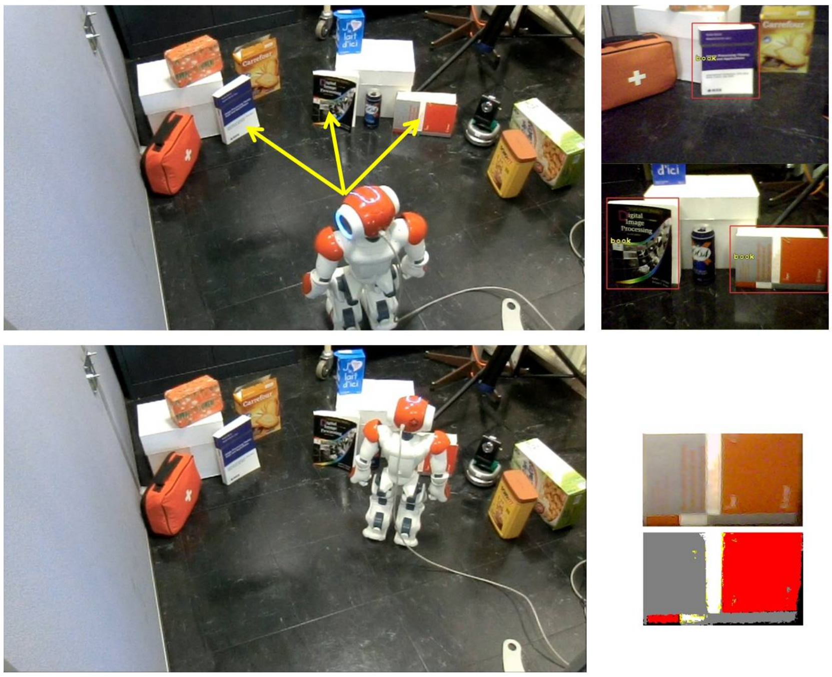

FIGURE 5.4.5: Exemple de résultat expérimental où le robot utilise les connaissances acquises pour différencier des objets similaires.

Chapitre 6

Robotique et système cognitif distribué

6.1 Introduction

Depuis maintenant plus d'une trentaine d'années, les systèmes multi-robots sont devenus progressivement un axe de recherche à part entière de la robotique. Généralement, ces systèmes multi-robots peuvent se diviser en deux grandes catégories. La première est celle des systèmes composés d'un ensemble de robots homogènes. Dans cette catégorie, on retrouve la robotique en essaim qui s'inspire des phénomènes de groupe du monde animal (colonie de fourmi, banc de poisson, etc..) ainsi que les systèmes reconfigurables [Butler 08]. Bien qu'en apparence les problématiques semblent différentes, dans les deux cas, on cherche généralement à étudier l'émergence de comportements complexes d'un groupe à partir du comportement individuel de chaque entité. La deuxième catégorie correspond aux systèmes multi-robots hétérogènes regroupant des robots pouvant avoir des caractéristiques très différentes et dont le but est de coopérer pour réaliser une ou plusieurs tâches complexes [Parker 08b]. Dans ce cas, les aptitudes des robots sont généralement complémentaires.

Les systèmes multi-robots sont par nature des entités matérielles distribuées dans l'espace mais pouvant interagir implicitement ou communiquer explicitement entre eux. Par conséquent, le contrôle d'un système multi-robots peut être soit centralisé lorsque l'ensemble des robots est contrôlé d'un point central, soit hiérarchisé dans le cas d'une structure pyramidale, soit décentralisé lorsque chaque robot est responsable de ses propres actions ou bien hybride lorsque l'on combine des stratégies de contrôles locaux avec des systèmes de supervision de plus haut niveau. D'un point de vue applicatif, les systèmes multi-robots offrent de nombreux avantages et peuvent contribuer à l'amélioration de l'efficacité des systèmes robotisés. Premièrement, les systèmes multi-robots permettent de décomposer une tâche complexe en plusieurs tâches plus simples. Dans ce cas, un ensemble de robots hétérogènes, capables de réaliser des tâches simples mais différentes, doivent coopérer pour effectuer une tâche plus complexe. Deuxièmement, on peut aussi utiliser un ensemble de robots homogènes répartis dans l'espace et travaillant en parallèle de manière à accroître la rapidité d'exécution d'une tâche. Enfin, l'utilisation de plusieurs robots permet d'accroître la robustesse car la défaillance d'un robot n'implique pas la défaillance des autres robots qui peuvent continuer à travailler.

Dans un système multi-robots, les interactions, explicites ou implicites, entre robots jouent un rôle très important et permettent d'ailleurs d'identifier plusieurs catégories [Parker 08a]. La figure 6.1.1 représente la classification proposée par Lynne E. Parker. Cette classification, qui utilise trois critères, décompose les systèmes multi-robots en quatre groupes. Le groupe nommé « collective interaction » concerne un ensemble de robots dans lequel chaque entité n'a pas conscience de la présence des autres entités mais où les robots partagent le même objectif. Les échanges sont donc purement implicites. La robotique en essaim représente un exemple type de cette classe. Dans les trois autres groupes, « cooperative interaction », « colaborative interaction » et « coordinative interaction », chaque robot est conscient de la présence de l'ensemble, ou du moins d'une partie, des autres robots. La différence entre chaque groupe repose sur le type d'objectif (individuel ou partagé) et sur le fait que les robots doivent collaborer ou bien se coordonner.

La classification proposée par Lynne E. Parker repose sur le principe de l'intelligence distribuée et des interactions entre chaque robot. Or bien que par nature un système multi-robots soit réparti dans plusieurs entités physiques, nous considérons qu'il est possible de l'aborder sous la forme d'un seul système cognitif. Et même si l'idée d'un système cognitif distribué semble absurde dans le cas d'un système biologique, les technologies de l'information et de la communication offrent la possibilité à un système artificiel de percevoir l'environnement et de contrôler des actionneurs à distance. Il est donc tout a fait envisageable d'imaginer un système cognitif distribué où les processus cognitifs conscients et inconscients sont en partie dissociés et répartis sur des entités matérielles différentes distribuées dans l'espace. De ce point de vue, le système, dans sa globalité, perçoit et agit sur son environnement via l'ensemble des capteurs et des effecteurs de l'ensemble des robots. Pour un robot « lambda », les autres robots font partie intégrante de l'environnement. Les PCI assurent à chaque robot une certaine autonomie, les PCC permettent au système multi-robots de se développer et de s'organiser. Dans la suite de ce cha-

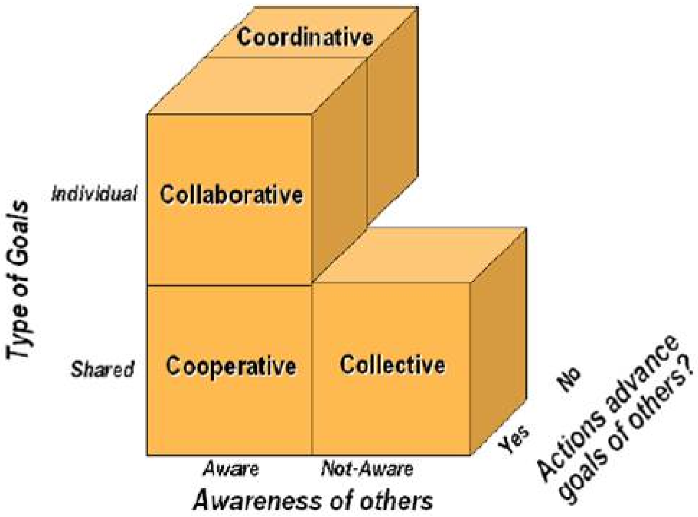

FIGURE 6.1.1: Classification des systèmes multi-robots en fonction des interactions au sein du groupe (extrait de [Parker 08a]).

pitre, les sections 6.2 et 6.3 seront consacrées respectivement à la description du système cognitif artificiel distribué et la présentation des résultats obtenus. Il est à noter que ces travaux ont fait l'objet de la thèse de Ting WANG [Wang 12a] et ont été publié dans [Wang 12b] [Wang 13].

6.2 Système cognitif artificiel distribué

La figure 6.2.1 représente une schématisation de notre système cognitif distribué dédié au contrôle d'un système multi-robots. Ce système est constitué d'un réseau d'agents (robots, capteurs, etc..) possédant chacun un système cognitif inconscient indépendant les uns des autres, mais sous le contrôle d'un seul système cognitif conscient. Par conséquent, chaque robot est en mesure de réaliser des comportements individuels complètement autonomes via ses propres capacités d'interaction avec son environnement, ou bien collectifs en utilisant des communications implicites entre robots. Le rôle du système cognitif conscient est alors de « superviser » l'ensemble du réseau via des communications explicites pour réaliser des tâches complexes. Cette approche a été mise en œuvre lors de la thèse de T.Wang qui avait pour but d'élaborer des stratégies de contrôle intelligent pour des systèmes multi-robots dans le cadre plus particulier de la logistique industrielle. Le contexte applicatif de cette étude consistait à coordonner une formation de robots coopérant dans le but de transporter une charge d'un point A vers un point B.

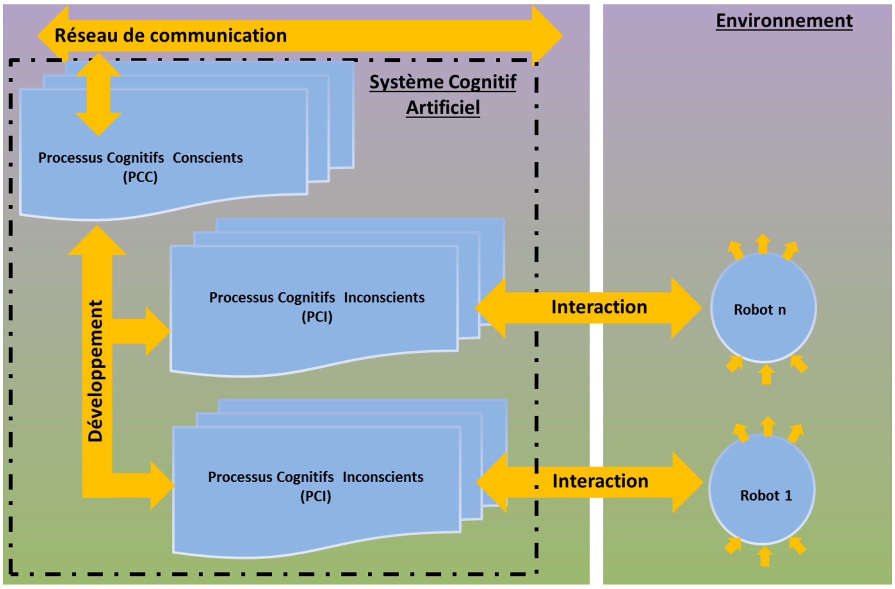

FIGURE 6.2.1: Schématisation du système cognitif artificiel distribué utilisé pour contrôler un système multi-robots. Les PCI assurent à chaque robot une certaine autonomie, les PCC permettent au système multi-robots de se développer et de s'organiser

Dans le cadre des recherches faites sur les systèmes multi-robots, de nombreux travaux se sont focalisées sur la commande des formations de robots. Dans ces travaux, l'idée centrale correspondait souvent à l'élaboration d'une stratégie de contrôle des robots pour la constitution, le maintien ou l'adaptation d'une formation représentant une structure géométrique. Dans notre cas, nous avons préféré nous concentrer sur une approche de plus haut niveau. Pour cela, nous avons supposé que tous les robots étaient contrôlés de manière synchrone et qu'ils évoluaient simultanément afin de conserver une structure virtuelle rigide ce qui permettait de considérer l'ensemble des robots comme une seule entité. Par conséquent, le contrôle individuel de chacun des robots pour maintenir ou modifier la structure géométrique de la formation n'a pas été abordé. Dans ce contexte, l'approche que nous avons alors proposée se base sur une modélisation discrète de l'environnement ainsi que sur la définition d'un ensemble d'actions fini pour le contrôle de la formation de robots comme par exemple « avancer », « reculer », « aller à droite », « aller à gauche », etc... Les actions qu'il était nécessaire d'exécuter pour déplacer la formation se déterminaient via un apprentissage par renforcement.

Dans un deuxième temps, nous avons étendu notre approche à un système multi-robots hétérogènes. L'infrastructure, de type réseau, que nous avons proposée regroupait, entre autres, une caméra mobile afin d'obtenir une image de l'environnement, un robot humanoïde pour guider la formation de robots et plusieurs robots non-holonomes pour transporter la charge et un ordinateur distant qui prenait en charge une partie des calculs. L'idée majeure de cette deuxième partie du travail était donc de considérer que les robots évoluaient dans un environnement plus réaliste, non connu à priori et avec d'éventuelles contraintes dynamiques. Le robot humanoïde, équipé de moyens de perception, et capable de communiquer avec des systèmes distants (réseau de capteurs par exemple), était chargé de contrôler cette formation. A partir d'une approche par systèmes à événements discrets (réseau de pétri), nous avons alors proposé une solution où un robot humanoïde supervisait, en fonction de l'environnement, le contrôle d'une formation de robots. D'un point de vue cognitif, ce robot était donc doté d'un système cognitif conscient permettant d'adapter le comportement du groupe en fonction de l'évolution dynamique de l'environnement.

L'ensemble de cette étude a été validé par de nombreuses simulations ainsi que par des résultats expérimentaux. Les principaux résultats obtenus montrent donc qu'il est possible d'utiliser une formation de robots virtuellement rigide pour déplacer un objet en tenant compte des contraintes de l'environnement (passage étroit, obstacles, etc..). La section suivante sera consacrée à la présentation de quelques résultats expérimentaux.

6.3 Principaux Résultats Expérimentaux

La plate-forme multi-robots hétérogène qui a été mise en œuvre lors de la thèse de T. Wang était composée d'un robot humanoïde robot (Nao), de plusieurs robots roulants non-holonomes (KheperaIII), d'une caméra IP, l'ensemble étant connecté à un ordinateur distant via un réseau sans fil. En effet, pour des raisons pratiques, une grande partie des calculs a été déportée sur l'ordinateur. Tous ces appareils pouvaient donc communiquer entre eux en échangeant des données. La caméra IP permet d'obtenir un point de vue global de l'environnement à traverser. L'ordinateur permettait quant à lui de planifier le chemin de la formation de robots et transmettait au robot Nao l'ensemble des commandes nécessaires à la bonne exécution de la tâche. Le but du robot humanoïde est de « guider », en fonction des contraintes de l'environnement (e.g. obstacle intempestifs, passage étroit, etc...) les robots KheperaIII qui transportent la charge. La figure 6.3.1 illustre les plateformes multi-robots virtuelles et expérimentales. Les simulations ont été réalisées à l'aide du logiciel Webots associé à Matlab.

Pour transporter une charge entre deux points, l'ordinateur distant, qui joue

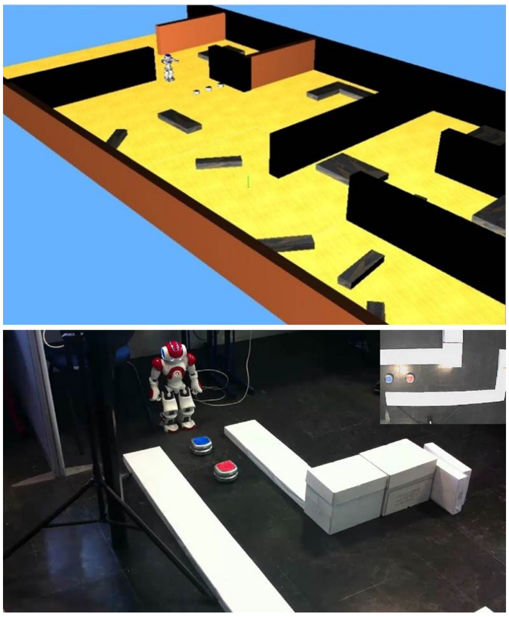

FIGURE 6.3.1: Illustration des systèmes multi-robots virtuels (en haut de la figure) et expérimentaux (au bas de la figure).

ici le rôle de superviseur, commence par récupérer une image de l'environnement via la caméra IP. Sur cette base, le superviseur calcule la trajectoire et détermine l'ensemble des commandes (par exemple « go forward », « left », etc) permettant de contrôler la formation des robots. Pendant la durée du déplacement, le robot Nao, à partir de la liste des commandes transmises par le superviseur, supervise les déplacements des robots KheperaIII (voir Fig. 6.3.2). En l'absence d'obstacle, tous les robots avancent simultanément en direction de la position désirée en maintenant toujours la même formation. Mais, en présence d'obstacle, le robot Nao peut intervenir pour stopper la formation ou demander une nouvelle planification pour contourner cet obstacle (voir 6.3.3).

D'un point de vue cognitif, on peut donc considérer les robots non-holonomes comme des exécutants dotés simplement d'un système cognitif inconscient qui sont, d'une part, capables d'interagir implicitement entre eux pour maintenir une formation, et d'autre part, aptes à exécuter des ordres transmis de manière explicite par un système cognitif distant (Robot Nao associé à un ordinateur), de plus haut niveau (système cognitif conscient), destinés à diriger ou modifier la structure de la formation.

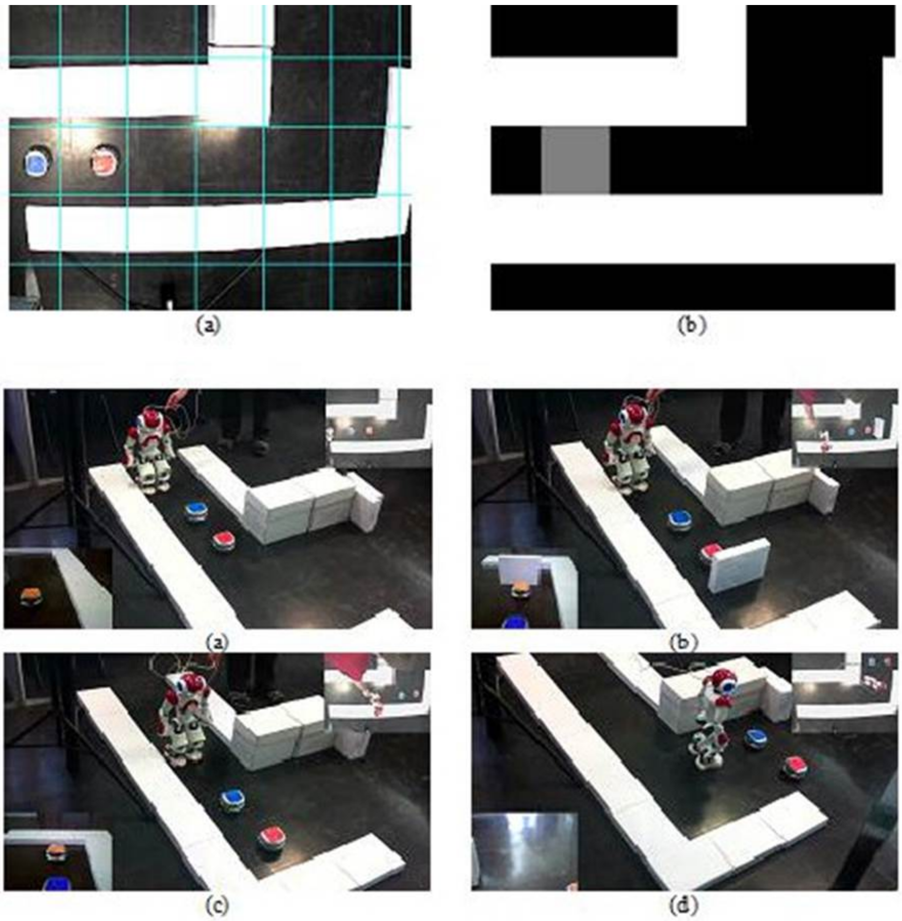

FIGURE 6.3.2: A partir de l'image fournie par la caméra IP, placée approximativement à 2 mètres au dessus des robots, le superviseur calcule la trajectoire (haut de la figure). Pendant la durée du déplacement, le robot Nao supervise les déplacements des robots KheperaIII (bas de la figure).

FIGURE 6.3.3: En présence d'obstacles, le robot Nao peut intervenir pour stopper la formation ou demander une nouvelle planification pour contourner cet obstacle.

6.4 Conclusion

Dans ce chapitre, j'ai introduit la notion de système cognitif distribué où les processus cognitifs conscients et inconscients sont répartis entre plusieurs entités matérielles différentes distribuées dans l'espace. Ce système perçoit et peut agir sur son environnement à distance via l'ensemble des capteurs et des effecteurs des différents robots. Ce système a été utilisé dans le cadre d'un système multi-robots dédié au transport de charges en logistique. Bien que nous n'ayons pas abordé le contrôle individuel de chacun des robots pour maintenir ou modifier la structure géométrique de la formation, le contexte applicatif étudié démontre qu'il est tout à fait envisageable d'utiliser un système cognitif distribué pour contrôler des systèmes multi-robots. Les résultats obtenus dans les chapitres précédent 4 et 5 concernant respectivement, l'acquisition de nouvelles capacités motrices, la perception et la conceptualisation de connaissances sont bien sûr exploitables. Mais une approche distribuée permet aussi d'envisager des perspectives comme la perception collective d'un environnement complexe impliquant plusieurs entités ; chacune ayant une perception restreinte de son environnement. Il serait aussi intéressant de pouvoir exploiter des capteurs, associés aux différentes entités pour percevoir l'environnement avec un maximum de connaissances fiables afin d'en faire émerger une connaissance collective. Les applications des systèmes cognitifs distribués sont donc nombreuses et peuvent concerner notamment les systèmes ubiquitaires à la robotique de service et d'assistance à la personne.

Conclusion et perspectives

Si au 20ème siècle, robotique était souvent synonyme de machines automatisées dotées d'aucune sensibilité et travaillant continuellement dans des usines, le 21ème siècle sera très certainement le siècle qui verra l'émergence et le développement de la robotique service. Que le cadre soit celui de la robotique de service à usage personnel ou bien celui à usage professionnel, ces robots omniprésents seront destinés à interagir régulièrement avec des êtres humains pour les aider au quotidien. Ils devront faire preuve d'une très grande souplesse d'adaptation en développant, au fil de leurs expériences, de nouvelles compétences en adéquation avec leurs missions. Les difficultés liées au développement de robots de service, en contact quasi-permanent avec des êtres humains, ne viendront pas directement de la complexité des tâches qu'ils devront accomplir mais plutôt de la diversité des contextes dans lesquels ils devront le faire. Le développement économique de la robotique de service et d'assistance à la personne sera donc intimement lié au fait que les robots posséderont la capacité à s'intégrer naturellement dans leur environnement afin de cohabiter intelligemment avec les êtres humains. Le fil conducteur des recherches qui ont été présentées dans ce mémoire s'est appuyé sur l'idée qu'un robot peut acquérir progressivement des connaissances, des compétences nouvelles. L'idée n'est donc pas de développer un robot « intelligent », mais plutôt de concevoir un robot qui soit capable de le devenir au contact des êtres humains. Dans ce contexte, nous avons proposé une approche originale qui s'inspire de la robotique développementale et plus particulièrement de la théorie de l'énaction. L'originalité du travail qui a été présenté dans ce mémoire consiste à décomposer le Système Cognitif Artificiel (SCA) en deux parties distinctes : une regroupant des Processus Cognitifs Inconscients (PCI) et l'autre des Processus Cognitifs Conscients (PCC). Bien que ce mémoire n'avait pas pour ambition de définir une architecture cognitive complète permettant à un robot de devenir « intelligent », il a permis de présenter des exemples concrets de mise en œuvre d'un système cognitif artificiel pour l'acquisition d'aptitudes motrices complexes ainsi que l'acquisition et la conceptualisation de connaissances. D'autre part, ce mémoire nous a aussi permis d'introduire le concept de système cognitif distribué où les processus cognitifs conscients et inconscients sont répartis entre plusieurs entités matérielles différentes distribuées dans l'espace. Les approches développées pour l'acquisition de nouvelles capacité motrices ou bien la perception et la conceptualisation de connaissances sont bien sûr exploitables sur les systèmes distribués.

Les perspectives de ce travail peuvent s'inscrire pleinement dans le domaine de la robotique de service. Ce domaine de la robotique, destiné à l'assistance des personnes à domicile, peut se scinder en deux grandes catégories qui sont d'ailleurs complémentaires. Les chercheurs de la première catégorie se concentrent sur la conception de robots compagnons tout en un, le plus souvent sous la forme d'un robot humanoïde, capable de répondre à l'ensemble des besoins dont un être humain a besoin. Dans ce cas, on privilégie l'interaction, voire la coopération, entre l'homme et le robot de manière à ce que le robot aide l'être humain dans l'exécution de certaines tâches de la vie quotidienne. Les chercheurs de la deuxième catégorie préfèrent se focaliser sur le développement de systèmes robotiques ubiquitaires qui s'appuient sur l'interconnexion des systèmes et l'accès à internet via des réseaux informatiques pour créer des espaces intelligents. Dans ce cas, l'objectif consiste plus à améliorer la sécurité et le confort des personnes. La robotique ubiquitaire destinée au service et à l'assistance à la personne représente donc un domaine d'application adéquate aux systèmes cognitifs distribués et correspond à certaines thématiques de recherche du LISSI.

La restructuration thématique du LISSI autour d'applications dans le domaine des technologies pour la santé a conduit à la création de plusieurs groupes thématiques dont le groupe SIRIUS (Systèmes Intelligents, RobotIqUe ambiante et de Service) et le groupe SYNAPSE (SYstèmes cogNitifs Artificiels et Perception Bio-InSpiréE). Les thématiques de recherches du groupe SIRIUS sont axées sur les systèmes ubiquitaires et plus particulièrement sur le développement, la modélisation et le contrôle-commande de systèmes intelligents ambiants et robotiques pour l'assistance aux personnes dépendantes (personnes âgées, patients). Les activités du groupe SYNAPSE s'inscrivent, quant à elles, principalement autour des thématiques complémentaires de la Perception bio-inspirée et de la Cognition Artificielle. L'orientation scientifique du groupe est illustrée par des études et validations expérimentales autour des fondements clés de la perception, de la cognition et de la conceptualisation de connaissances. La complémentarité de ces deux groupes permet d'envisager le développement d'une recherche transversale ayant pour objectif le développement d'applications pour robots compagnons interconnectés avec un réseau ubiquitaire permettant ainsi de créer des environnements ou écosystèmes intelligents pouvant améliorer la qualité de vie, l'état physique et mental, et le bien-être social des usagers en offrant une multitude de services. Dans ce cas, un verrou scientifique important concerne la coordination et la coopération de ces écosystèmes intelligents via une intelligence distribuée.

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III - Publications annexées

Multi-level cognitive machine-learning based concept for human-like "artificial" walking : Application to autonomous stroll of humanoid robots

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Multi-level cognitive machine-learning based concept for human-like "artificial" walking: Application to autonomous stroll of humanoid robots

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ABSTRACT

We propose a machine-learning based multi-level cognitive model inspired from early-ages' cognitive development of human's locomotion skills for humanoid robot's walking modeling. Contrary to the most of already introduced works dealing with biped robot's walking modeling, which place the problem within the context of controlling specific kinds of biped robots, the proposed model attends to a global concept of biped walking ability's construction independently from the robot to which the concept may be applied. The chief-benefit of the concept is that the issued machine-learning based structure takes advantage from "learning" capacity and "generalization" propensity of such models: allowing a precious potential to deal with high dimensionality, nonlinearity and empirical proprioceptive or exteroceptive information. Case studies and validation results are reported and discussed evaluating potential performances of the proposed approach.

1. Introduction

The term "cognition", derived from the Latin word "*cognoscere*", which means "to know" or "to recognize", refers to the ability for the processing of information applying knowledge. If the word "cognition" has been and continues to be used within quite a large number of different contexts, notably in the fields of linguistics, anesthesia (e.g. reversible lack of awareness [1]), neurology, psychology, philosophy, anthropology, systemic and computer science, it often intends the intellectual activities and processes relating the "awareness" and to the realized knowledge-based issued "intelligent" functions.

Within psychology or philosophy, the concept of cognition is closely related to abstract concepts such as "mind", "reasoning", "perception", "intelligence", "learning" and other concepts describing capabilities of the human mind. In artificial intelligence, this concept is used to refer to the mental-like (inspired from human) artificial functions, mental-like artificial processes and states of "intelligent entities" (machine's human-like organization or highly autonomous machines). In present paper, we focus this last notion of "cognition": human-like functionality (behavior) of humanoid machines (robots) and their autonomy. It is relevant to notice that during the last decade, as well humanoid robotics as human-like behavior have been subject to an ever-increasing interest and have been origins of numerous works. However, the most of works relating humanoid robotics have concerned either the design of controllers (controlling different devices of such robots in order to maintain equilibrium or to reach desired actions of the components constituting such robots) or the navigation aspects [2–8]. In the same way, major part of works dealing with human-like behavior is connected with abstract tasks, as those relating reasoning inference, interactive deduction, etc. [9–22]. Inspired by juvenile (early) ages human's skills developments, we accost the above-mentioned skills from a different slant directing our attention to both "unconscious cognitive functions" (UCF: that we identify as "instinctive" cognition level handling reflexive abilities) and "conscious cognitive functions" (CCF: that we distinguish as "intentional" cognition level handling thought-out abilities).

A typical example of UCF is human's (biped) walking. Human constructs this complex skill during his early ages. During his first year, the human (baby) is busy developing coordination and muscle strength throughout his body. He will learn to sit, to roll over, and to crawl before moving on to pulling up and standing at about 8 months [23]. Then, he will refine the matter gaining confidence and balance. After those first key steps toward independence, baby will begin to master the finer aspects (points) of mobility [23,24]: by 18 months and up to 25 months, likely, the baby will become a proficient walker and he will begin to climb or probably to motor up stairs though he will still need help getting back down. He may try to kick a ball, even if he won't always be successful. Then, and until his third birthday his basic movements will become more and more reflexive (second nature) allowing him no longer need to focus energy on walking, standing, running or

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jumping [25,26]. What is interesting to note here (e.g. from this example) is that constructed (acquired) as a result of a plenty cognitive process, the perfunctory task of biped's walking grows to be unconscious. That is why we distinguished outcomes of such kind of cognitive processes as UCF.

Let us now continue extending the above-considered example to the "biped locomotion" task. In fact, if the aforementioned reflexive functions are inescapable for reaching biped's complete walking process, they are not enough to get hold of biped locomotion's sophistication of the human. To obtain such refinement additional cognitive skills are required. We have categorized this additional level as what we called "conscious cognitive functions" (CCF). A typical example is the obstacle avoidance and navigation abilities of the human constructing since his juvenile ages. Considering the obstacle avoidance fitness, besides reflexive fluency, it requires intellectual acquaintance relating notions as "estimation" (relating obstacle's size and distance between actual position of the biped and the obstacle, etc.), "interaction" with environment (integrating the fact that the obstacle belongs to the environment in which the biped evolves and not a part of his own body), "decision" (choice or deduction leading to the appropriated avoidance strategy or action: as to make choice between "stepping over" the obstacle and "modifying the walking direction" or deciding about the adequate "step length" in order to successfully step over the obstacle, etc.). It is pertinent to notice that CCF may include several levels corresponding to "primary" or "high-level" attitudes. For example the basic obstacles avoidance function could be seen as "primary-level" CCF, while the navigation, which involves skills such as space–time representation (modeling), self-localization (etc.), could be seen as "high-level" CCF. It is also pertinent to notice that a given conscious cognitive task may evolve from primary to high-level CCF requirement. For example, if mundane obstacle stepping over or avoidance is as primary-like CCF, the same task becomes a high-level CCF when, for example, it is performed within the frame of sportive context. What is interesting to emphasize here (e.g. from these examples) is that construction of such cognitive processes in biped's walking is clearly conscious. That is why we differentiate their outcomes as CCF. Finally, let us remind that according to an ever-increasing number of recent works, the intellectual cognitive abilities appear (are developed) since early ages of human being [27,28]. Accordingly to those interesting recent investigations, it seems that, in fact, as soon as the baby acquires his first decisive independency thanks—to regulating the sitting, rolling over and crawling (e.g. since the sixth month of his existence), he begins to develop his first intellectual (reasoning and even mathematical) skills [27–31]. This important point reinforces our conviction that the sophistication of the human's biped walking begins at the same time that he perfects his reflexive walking ability: in other words, UCF and CCF are inseparable (and inescapable) bare bones in construction of human's walking ability, and thus unavoidable in exploration toward the humanoid robots' "artificial" walking achievement.

Based on the aforementioned statements (and related works), we propose a machine-learning based multi-level cognitive model inspired from early ages' cognitive development of human's locomotion skills for humanoid robots' walking. At odds with the most of already introduced works dealing with biped robot's walking modeling, which place the problem within the context of controlling specific kinds (specific implementations) of biped robots, the proposed model attends, at the same time, to a global concept of biped walking ability's construction independently from the robot to which the concept may be applied. Indeed, the major available works (including our own previous works) gaze the problem within the control theory's slant: references [32–39] are good examples of this tendency. If today several prototypes, among which the most remarkable are undoubtedly the robots Asimo [40,41] and HPR family (HRP-2 to HPR-4c ([42–45]), have proved the feasibility of humanoid robots' walking, the locomotion of humanoid robots remains a big challenge: of course, these biped robots are able to walk but their basic locomotion tasks are still far from equalizing the human's dynamic locomotion process. The origins of the intricacy are multiple. Among numerous facts, one can emphasize: the fact that biped robots are high-dimensional non-linear systems, the truth that the contacts between robot's feet and the "real ground" are unilateral (e.g. very complex to model), the fact that biped robots are intrinsically not statically stable during the walking, and finally, the necessity to take into account of "exteroceptive" information (e.g. information relating environment in which robot evolves and objects with which robot interacts). Moreover, for most of them, the proposed or implemented models, as well as issued techniques, are restricted to be applicable to those robots only.

Our multi-level cognitive concept attempts to surround the humanoid robots' "artificial" walking and the above-mentioned difficulties by supplanting the problem from the "control theory" backdrop to the "cognitive machine learning" backcloth, slotting in two kinds of cognitive levels: "unconscious cognitive level" generating what has been called UCF and "conscious cognitive level" (susceptible to include several sub-levels) responsible of what has been identified as CCF. The first key-advantage of conceptualizing the problem within such incline is to detach the build-up of artificial biped walking from the type of robot: as the early age human's walking ability's development which in its global achievement doesn't depend on kind of "baby". The second chief-benefit of the concept is that the issued structure is "machine learning" (artificial neural networks, fuzzy logic, reinforcement learning, etc.) based foundation taking advantage from "learning" capacity and "generalization" propensity of such models: allowing a precious potential to deal with high dimensionality, nonlinearity and empirical (non-analytical) proprioceptive or exteroceptive information.

The next section of the article is devoted to the proposed Multi-level cognitive concept. The third section of the paper is dedicated to validation of the proposed concept. Examples of UCF, CCF are reported and discussed evaluating potential performances of our approach. Finally, fourth section concludes the paper and plans ahead further perspectives of the presented research work.

2. Multi-level cognitive machine-learning based "artificial" walking concept

Before detailing the proposed artificial walking concept, it is relatable to point up the fact that we centre the cognitive nature (in sense of "operating applying knowledge") of our concept on the one hand, on learning based construction of involved functions and on the other hand, on generalization flowed functioning of issued models (functions). So, "machine learning" (ML) and related techniques play a central role in our approach. Taking into account this fact, the proposed concept considers artificial biped walking process as a multi-model structure where involved component (models, functions, etc.), constructed as a result of ML, handle two categories of operational levels: reflexive and intentional. According to what has been mentioned in introductory section, two kinds of "elementary functions" (EF), so-called UCF and CCF, will build-up functional elements ruling the artificial walking task. Fig. 1 illustrates the bloc diagram of the proposed cognitive artificial biped walking conception. As it is noticeable from in this figure, within the proposed concept, the overall architecture of the artificial walking is obtained by building up cognitive layers (levels) corresponding to different skills fashioning the walking talent, which enclose a number of "elementary functions". Within such a

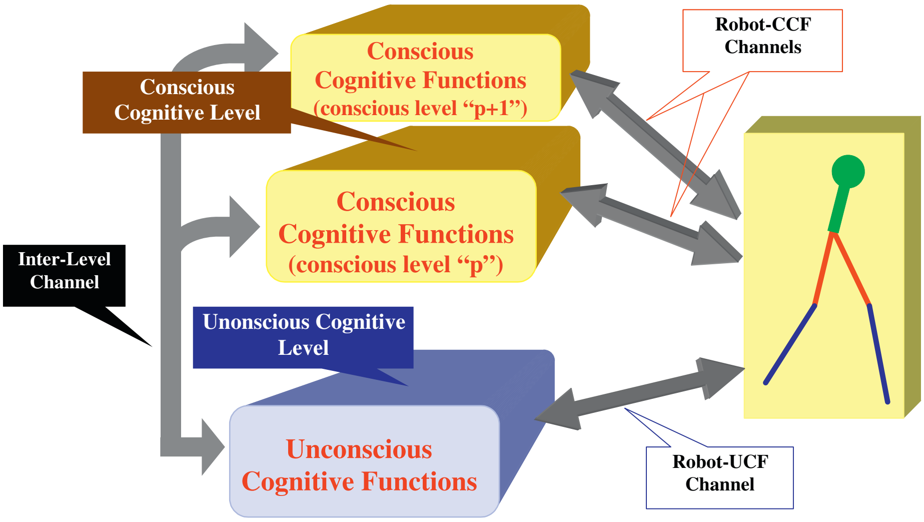


Fig. 1. General bock diagram of cognitive artificial biped walking conception.

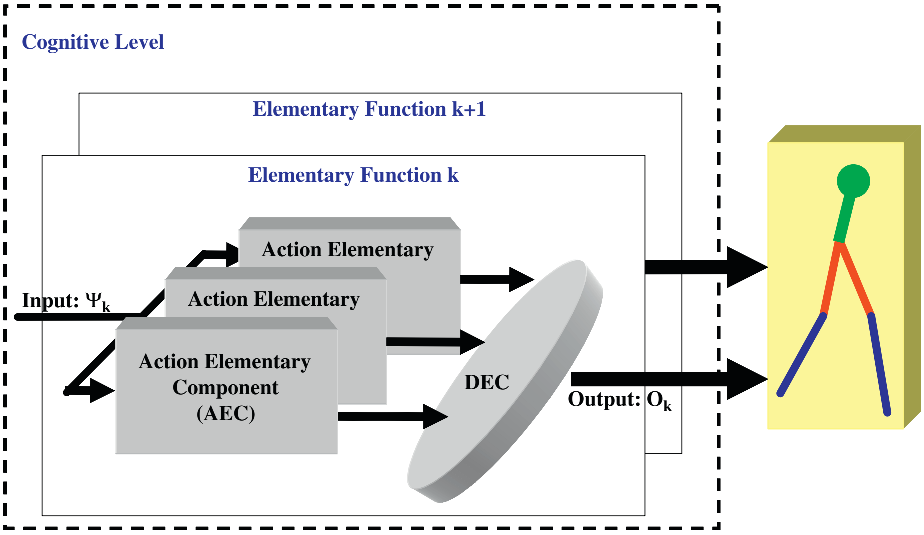


Fig. 2. General bock diagram of an elementary function (EF).

scheme, a cognitive layer may fulfil a skill either independently from other layers (typically, the case of unconscious cognitive levels) or using one or several talents developed by other layers (characteristically, the case of conscious cognitive levels).

Let us first describe what "elementary functions" (EF) are. We define EF as the lowest level learning-issued function realizing an elementary skill relating (e.g. necessary for) the walking. An EF is composed of what we define as "elementary component" (EC). We define (identify) two kinds of EC: the first corresponding to elementary action that we call "action elementary component" (AEC) and the second corresponding to elementary decision that we call "decision elementary component" (DEC). Both of these two kinds of EC are knowledge-based components. An EF may include one or both two kinds of the above-defined EC. Finally, an EF may include one or several EC. Fig. 2 gives the general bloc diagram of an EF. Supposing that a given cognitive level (either conscious or unconscious) includes K ($K \in N$ where N represents the "natural numbers" ensemble) elementary functions, considering the kth elementary function (with $k \in N$ and $k \leq K$), we define the following notations:

- Ψ_k the input of kth elementary function: $\Psi_k = [\psi_1,\ldots,\psi_j,\ldots,\psi_M]^T$ where ψ_j represents the input component of the jth EC of the kth EF, $j \leq M$ and M the total number of elementary components composing the kth EF
- O_k the output of kth elementary function
- o_j the output of the jth EC of the kth EF, with $j \leq M$ and M the total number of elementary components composing the kth EF
- $F_k(.)$ the function (skill) performed by the kth EF
- $f_j^A(\cdot)$ the function (transformation, etc.) performed by jth AEC
- $f^D(\cdot)$ the decision (matching, rule, etc.) performed by DEC

Within the above-defined notation, the output of the kth elementary function could be formalized as shown in (1) where o_j is obtained from Eq. (2). In a general case, the output of an EC may also depend to some internal (specific) parameters particular to that EC:

$$O_k = F_k(\Psi_k) = f^D(\Psi_k, o_1,\ldots,o_j,\ldots,o_M) \quad (1)$$

$$o_j = f_j^A(\psi_j) \quad (2)$$

For example the "gait pattern" (e.g. walking step) generation corresponding to walking on flat ground with a given velocity could be seen as a "flat-ground walking EF". So, in the generalization phase (e.g. operation phase meaning: after the ML based construction of the EF) the input parameter of such EF will be the "desired velocity" and its output will be the appropriated "walking step" (step length) ensuring the desired velocity. Here, it befalls important to underline a prominent specificity of the "learning" phase versus the "generalization" phase: in fact, during the learning phase the output (or related parameters) of EF may turn out to be the input parameters as well as it may occur that learning phase deals with a number of additional parameters inherent to the used ML model (as for example the "learning rate" in back-propagation based arterial leaning, etc.). In the case of the above-considered example, except the additional latent inputs exclusive to the used ML process, the desired "walking step" will become an additional input (beside the "desired velocity") fashioning the "estimated walking step" (output of the considered EF). Connecting the constitution of the above-considered EF, it may include several AEC (each corresponding, for example, to an elementary action of biped robot's internal devices) and at least one DEC performing the final (e.g. the appropriated) "walking step" (e.g. output). One has certainly remarked that the above-considered example corresponds to a reflexive function, and so will belong to UCF category. In the same way, an intentional EF (e.g. belonging to CCF category), for example handling the avoidance of either a "static" or a "moving" obstacle (with a given size), could be identified and constructed. In next section, precise examples of such UCF and CCF are given and discussed.

3. Case study and validation examples: towards autonomous stroll of humanoid robots

This section acquaints with validation of the above-presented concept. We have founded the validation on the basis of compulsory skills towards the autonomous stroll of humanoid robots. The required skills are constructed according to the above-described concept and are reported as case studies relating the previously described cognitive machinery. Two complete case studies are reported. The first one connects reflexive aspect of artificial biped walking, giving a detailed example (and corresponding results) of what we called "unconscious cognitive functions" (UCF). Sorting out intentional constituent of artificial biped walking, the second one gives an exhaustive example (and corresponding results) of what we called "conscious cognitive functions" (CCF). Nevertheless, let us first introduce the archetype of the biped robot. The below-described model will be used in order to construct learning databases corresponding to the human-like walking knowledge. This knowledge (gait patterns corresponding to: different situations, various walking velocities, various legs' arrangements, etc.) has been used as basis (simulated experimental data) to evaluate (validate) the proposed concept. This archetype of the biped robot (e.g. the issued virtual humanoid robot) has also been used in order to validate the proposed concept (e.g. to test the proposed cognitive model's issued behavior). However, it is pertinent to emphasize again that the proposed concept is applicable to any other kind of humanoid robot (Fig. 3).

3.1. Biped robot's model

The embodiment of the considered biped robot has been inspired from a real prototype: RABIT [46]. Although the abilities of RABBIT robot are limited in comparison to other humanoid robots, this under-actuated robot allows studying real dynamical walking leading to the design of new control laws in order to improve humanoid robots' current performances. Accordingly to this, our virtual robot is modeled as including a "trunk" and two legs (but no feet). Within such topology, the robot's dynamics could be modeled on the basis of five angles (one for trunk and two for each leg: q_0, q_{11}, q_{12}, q_{21} and q_{22}) and four torques (T^{sw}_{knee},T^{sw}_{hip},T^{st}_{knee},T^{st}_{hip}) applied to the knee and to the hip during the swing and stance phases, respectively [37]. q_{i1} and q_{i2} ($i \in \{1,2\}$) are the angles (e.g. angular positions) measured at the hip and the knee of the ith leg. K^p_{hip} and K^p_{knee} are amplitudes (gains) relative to position. $\dot{q}_{i1}$ and $\dot{q}_{i2}$ are, respectively, the measured angular velocities of hip and the knee of the ith leg. K^v_{hip} and K^v_{knee} are amplitudes (gains) relative to those angular velocities. q_0 and K^p_{trunk} correspond to the trunk's pitch angle (angular position) and the amplitude (gain) relative to this angle. $\dot{q}_0$ is the trunk's angular velocity and K^v_{trunk} the amplitude (gain) referring to that angular velocity. Finally, q_{r1} and $\dot{q}_{r1}$ are the relative angular position and the corresponded angular velocity between the two thighs, respectively. Fig. 4 gives the bloc diagram of the biped model, showing references for the angles and the torques. The complete dynamical model of such virtual biped robot is described in our previous publications [37]. Here, we just sum up the essential features of the model.

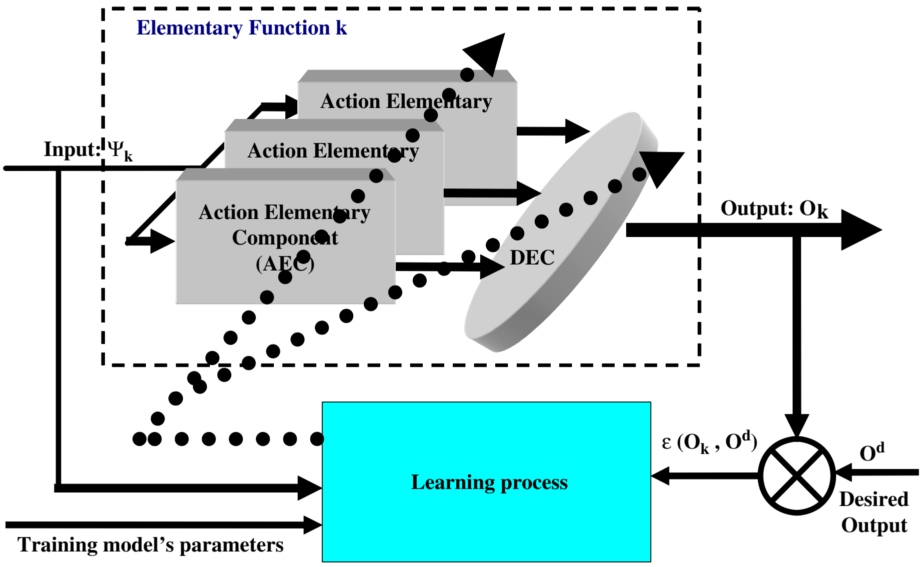


Fig. 3. General bock diagram of an elementary function's learning, where Ψ_k, O_k, O^d represent input of the kth EC, output the kth EC and desired output, respectively.

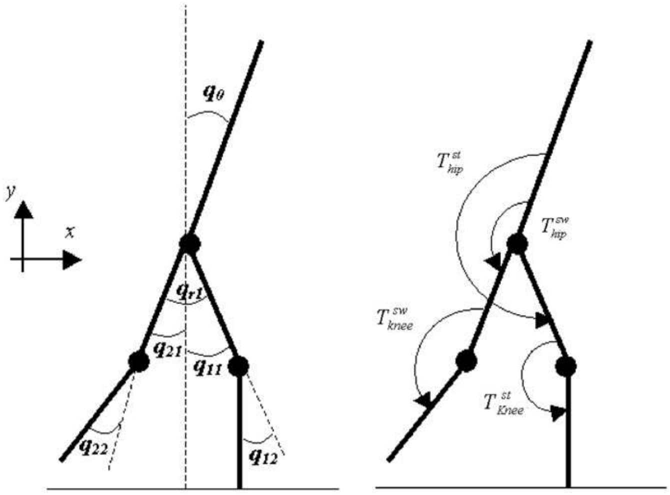


Fig. 4. Biped model indicating references for angles and torques.

The model assumes that the virtual robot includes different sensors (also virtual). Five sensors provide information relating the angles (one measuring the pitch angle of the trunk and four supplying relative angles between the trunk and the thigh for the hip, and between the thigh and the shin for the knee). Two binary virtual sensors detect whether or not the leg is in contact with the ground. Based on the information furnished by the sensors, it is possible to calculate the length of the step (L_{step}) when the two legs are in contact with the ground and the duration of the step (t_{step}: the duration from takeoff to landing of the same leg), which may be obtained from the contact sensors' information. Furthermore, it is possible to estimate the robot's average velocity (V_M) using Eq. (3).

$$V_M = \frac{L_{step}}{t_{step}} \tag{3}$$

Ignoring frictions (assuming that these effect are negligible), the legs' motions may be generated, within such model, as a chain (succession) of passive and active phases. Five intuitive rules (directly inspired from human-like walking) allow generating (simulating) a stable dynamic walking using the intrinsic dynamic of a real biped robot. The aforementioned five rules, corresponding to appropriated torques' computation [33], are shaped as the five next equations:

$$T^{sw}_{hip} = K^{p}_{hip}(q^{d}_{i1} - q_{i1}) - K^{v}_{hip}\left(\dot{q}^{d}_{i1} - \dot{q}_{i1}\right) \tag{4}$$

$$T^{sw}_{knee} = K^{p}_{knee}(q^{d}_{i2} - q_{i2}) - K^{v}_{knee}(\dot{q}^{d}_{i2} - \dot{q}_{i2}) \tag{5}$$

$$T^{st}_{hip} = K^{p}_{trunk}(q^{d}_{0} - q_{0}) - K^{v}_{trunk}\dot{q}_{0} \tag{6}$$

$$T^{st}_{knee} = -K^{p}_{knee}q_{i2} - K^{v}_{knee}\dot{q}_{i2} \tag{7}$$

$$\Delta q^{d}_{0} = K^{p}_{trunk}(V^{d}_{M} - V_M) - K^{v}_{trunk}\frac{d}{dt}(V^{d}_{M} - V_M) \tag{8}$$

It is thus possible to modify the length of the step and the average velocity varying the model's parameters. Consequently, this allows generating various reference gaits constituting reflexive gait patterns database (acting as training knowledge). This model has been implemented under the ADAMS (a product of MSC software) software. This software, from the mechanical system's modeling point of view (e.g. integrating information as: masses and geometry of the real robot's devices) is able to simulate the dynamic behavior of such a robot and namely to calculate the absolute motions of the platform as well as the limb relative motions when torques are applied on the joints.

3.2. Example of UCF: neuro-fuzzy UCF for acquiring reflexive walking attitudes

The case study aims to illustrate how the reflexive walking abilities' may be achieved within the frame of the concept introduced in Section 2. We remind that reflexive walking relates the robot's ability of walking without interacting with environment issued items (e.g. not considering object, obstacles, etc.). The humanoid robot is assumed to be conforming to the dynamics described in previous sub-section. An UCF is associated to some basic gait (e.g. straightforward walk) and unconscious level (layer) in handling the reflexive walking includes several of such functions. In this case study example, an UCF could be seen as a neuro-fuzzy module (function) where AEC (realizing elementary actions) are artificial neural networks and the DEC is a fuzzy logic based inference. If a UCF of such kind incorporates M elementary actions, then the UCF will include M Action-like elementary components and one DEC.

3.2.1. Architecture of neuro-fuzzy unconscious cognitive function in charge with "flat-ground walking"

In view of what has been stated in Section 2 concerning the designed conception and referring to the robot's model (described in the previous sub-section) which involves, for each leg, the angular position and the angular velocity, an EC (e.g. elementary component) of such UCF will include four internal modules: two for angular position and two for angular velocity. In this example each internal module of an AEC is a single-input-single-output (SISO) CMAC like neural network ([47–49]). Thus the issued AEC will be also a CMAC based structure. Fig. 5 shows the bloc diagram of such CMAC based ACE which includes four internal modules (Fig. 5a). It also illustrates such ACE in training posture (Fig. 5b). We will note such CMAC based ACE by: $CMAC^j$.

In this example, we suppose that $M=5$ (so, $j \in \{1, 2, 3, 4, 5\}$), meaning that the issued UCF is composed of five AEC and one DEC. The actions of AEC (so-called $CMAC^1$ to $CMAC^5$, respectively) correspond to fives reference step lengths corresponding to five desired average velocities of the robot. Fig. 6 illustrates the general bloc diagram of the issued "flat-ground walking" UCF and Fig. 7 gives the detailed bloc diagram of this UCF. In Fig. 6, one can also remark the presence of another UCF, which is the "Average-velocity's control" UCF: in charge with the reflexive regulation of the robot's average walking speed. The DEC here is a well known Takagi–Sugeno fuzzy inference system (TS-FIS) based component [50]. Generally, the TS-FIS is described by a set of $R_k (k = 1\ldots N_k)$ fuzzy rules such as Eq. (9). $x_i (i = 1\ldots N_i)$are the inputs of the FIS with N_i the dimension of the input space. $A^j_i (j = 1\ldots N_j)$ are linguistic terms, representative of fuzzy sets, numerically defined by membership functions distributed in the universe of discourse for each input x_i. Each output rule y_k is a linear combination of input variables $y_k = f_k(x_1,\ldots,x_{Ni})$ (f_k is a linear function of x_i).

$$\text{if } x_1 \text{ is } A^j_1 \ldots \text{ and } \ldots x_i \text{ is } A^j_i \text{ then } y_k = (x_1,\ldots x_{Ni}) \tag{9}$$

Our fuzzy-CMAC based "flat-ground walking" UCF combines a set of CMAC neural networks using Takagi–Sugeno fuzzy inference system DEC. Consequently, such fuzzy-CMAC based UCF includes two input signals: Ψ and X. Ψ is the input signal which is applied on all the $CMAC^j$. $X = [x_1,\ldots,x_{Ni}]$ corresponds to the input vector of FIS. Mainly, the output of the obtained fuzzy-CMAC structure depends on the one hand on TS-FIS and on the other hand on the outputs of CMAC. The output Y is carried out in two stages:

First, the output of each CMAC^j is given by Eq. (10). D_j and W_j are, respectively, the binary associate vector and the weight vector of each:

$$o_j(\psi_j) = D_j(\psi_j)^T W_j \tag{10}$$

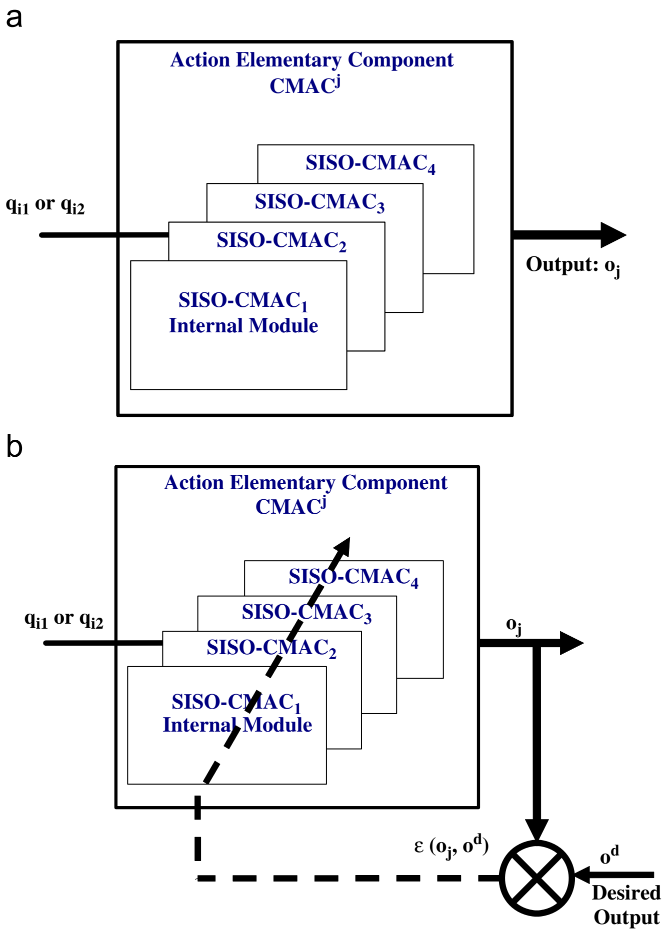


Fig. 5. Bloc diagram of internal module (Fig. 5a). It also illustrates such internal module in training posture (Fig. 5b).

Second, the output Y is estimated accordingly to Eq. (11). In fact, Y is computed using the weighted average of all CMAC outputs:

$$Y = O_k = \sum_j \overline{u_j} o_j(\psi_j) \tag{11}$$

In our case the input is the robot's average velocity and the output is the appropriated step length: this meaning that such UCF constructs the robot's step length ensuring the expected average velocity (when the robot walks reflexively performing a given average velocity). The fuzzy rules may be expressed as shown in Fig. 8, where V_{M_n} is the jth reference speeds (e.g. a particular magnitude of the average velocity) trained by the nth AEC constituting the UCF (e.g. by CMAC^j). Angular positions (q_{i1} and q_{i2}), and the two corresponding angular velocities ($\dot{q}_{i1}$ and $\dot{q}_{i2}$) are carried out by fusing the five aforementioned learned trajectories. This fusion is realized by using a FIS which is composed by the five following rules.

One can remark that the obtained UCF corresponds, in fact, to what is identified as human's unconscious walking regulating his walking speed (e.g. his average speed). It also should be notice that even if the function becomes reflexive (e.g. without any interaction with the environment) the concerned UCF has been constructed and operates using knowledge (learning, aggregating of the trained information): this function could thus be characterized as cognitive.

3.2.2. "Sloppy-ground walking" UCF: another example of neuro-fuzzy unconscious cognitive function

The same structure may extend the reflexive walking ability to the walking on sloppy ground (e.g. not flat) by creating additional appropriated UCF (as much as necessary). What is appealing, here, is that the structure of the UCF remains the same: the only changes concern the nature (e.g. kind) of the input. In fact, the learned feature is the step length (and the corresponding angular positions and speeds) but the input information will here is the ground inclination (slop).

3.2.3. Validation results

The validation has been performed on the basis of dynamics of a real biped robot (e.g. RABIT from which the archetype of the virtual biped robot has been inspired) described by [46] (see also [51] end [52]). The features of the real robot are reminded in Table 1. According to these features, a database containing different

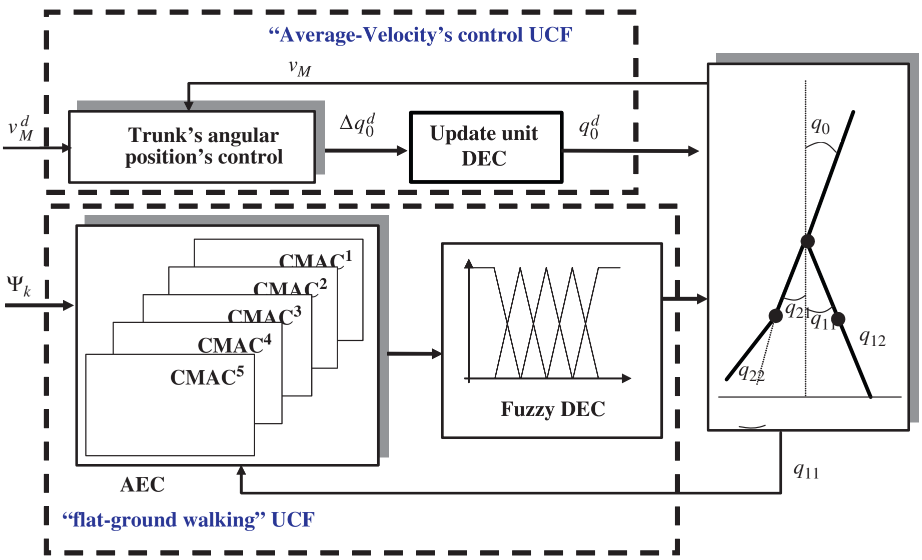


Fig. 6. General bloc diagram of the "flat-ground walking" UCF.

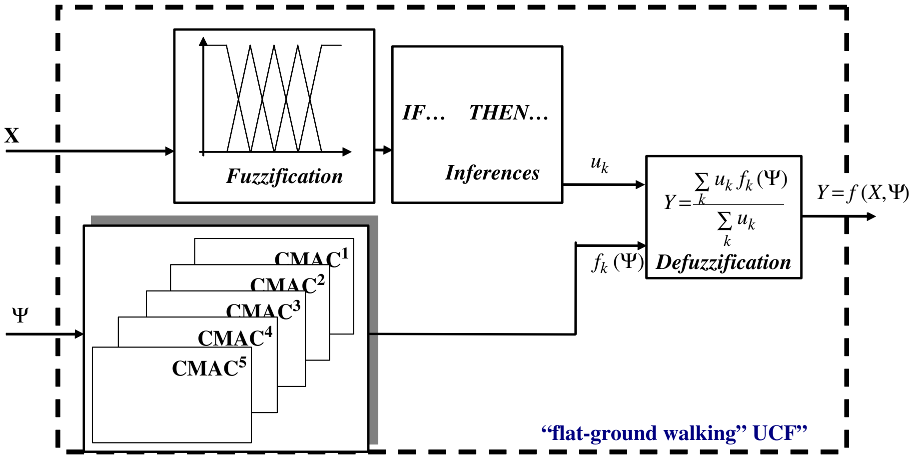
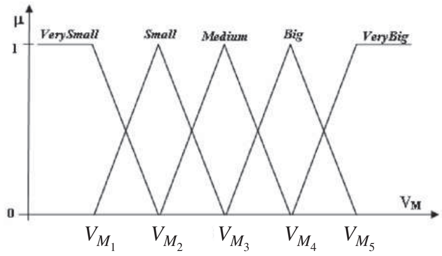


Fig. 7. Detailed bloc diagram of the "flat-ground walking" UCF.



- IF V_M is Very-Small THEN Y = o_1
- IF V_M is Small THEN Y = o_2
- IF V_M is Medium THEN Y = o_3
- IF V_M is Big THEN Y = o_4
- IF V_M is Very-Big THEN Y = o_5

Fig. 8. Example of the fuzzy membership rules' representation and corresponding linguistic rules.

Table 1
Robot's limb masses and lengths.

	Weight (kg)	Length (m)
Trunk	12	0.20
Thigh	6.8	0.40
Shin	3.2	0.47

Table 2
Reference gait patterns and corresponding features for "flat-ground" walking.

	V_M (m/s)	q^d_{r1} (deg.)	q^d_{sw} (deg.)	q^d_0 (deg.)	L_{step} (m)
CMAC[1]	0.4	20	−7	3.5	0.23
CMAC[2]	0.5	25	−10	3	0.28
CMAC[3]	0.6	30	−15	2.5	0.31
CMAC[4]	0.7	35	−20	8	0.36
CMAC[5]	0.8	40	−25	8	0.40

reference patterns has been generated using ADAMS simulation platform and the model described in sub-Section 3.1. This database includes reference length steps (and relate legs devices' angular positions and angular velocities) corresponding to various robot's average velocities for the flat ground walking situation as well as those features in the context of a sloppy ground (for different ground's inclines). Playing the role of the available knowledge concerning the human-like intuitive stroll, the above-mentioned database has been used to train SISO-CMAC neural networks.

Concerning "flat-ground" reflexive walking and the corresponding above-described UCF, the validation has been performed using reference patterns reported in Table 2 and the fuzzy membership diagram depicted by Fig. 9. The validation has been performed according to the following scenario: walking on a flat ground conformably to (e.g. respecting) an average velocity of 0.40 m/s (initial desired average velocity) during firsts 10 s, the robot receives the order to increase its average velocity up to 1 m/s (final desired velocity). Fig. 10 gives the validation results, showing waveforms corresponding to the desired average velocity, robot's average velocity and the generated length steps. It also gives the stick-diagram of the walking sequence corresponding to this validation scenario. It is pertinent to notice that the final desired average velocity has been reached (by robot) meaning that the robot has successfully adapted its length steps in order to comply

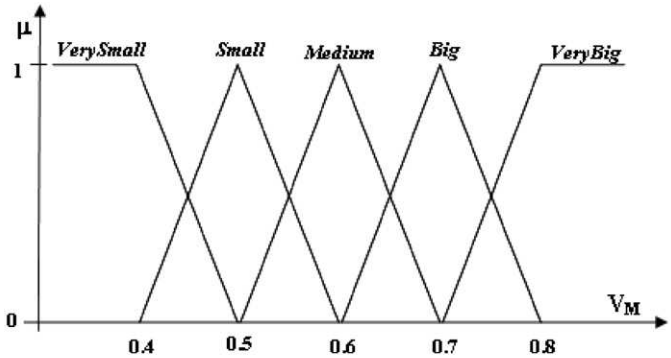


Fig. 9. The fuzzy membership shapes of flat-ground reference gait patterns.

with the new desired state. It is also relevant to give emphasis to the fact that the final state (e.g. walking respecting 1 m/s) is totally out of the range of the learned velocities, demonstrating a foremost generalization capability of the proposed concept.

The "sloppy-ground walking" ability has been evaluated accordingly to two scenarios: an ascendant walk and a downward

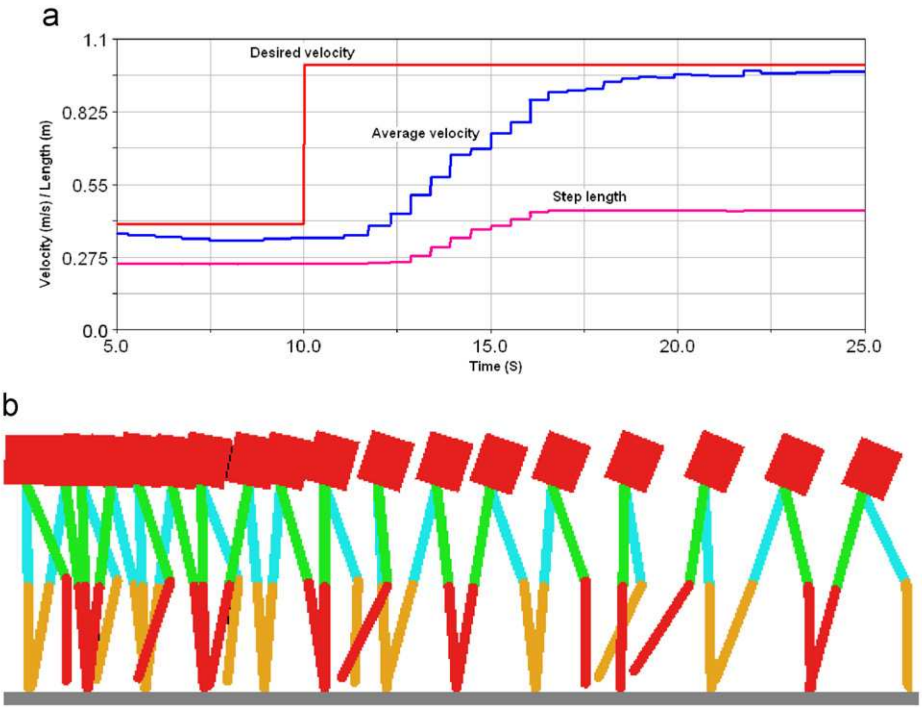


Fig. 10. Waveforms representing the desired average velocity, robot's average velocity and generated length steps (a) and stick-diagram (b) corresponding to the validation flat-ground walking scenario.

Table 3
Reference gait patterns and corresponding features for ''sloppy-ground'' walking.

	Slope (deg.)	q_{r1}^{d} (deg.)	q_{sw}^{d} (deg.)	q_{0}^{d} (deg.)
CMAC[1]	−4	34	−5	2.5
CMAC[2]	−2	30	−10	2.5
CMAC[3]	0	30	−15	2.5
CMAC[4]	+2	30	−20	2.5
CMAC[5]	+4	30	−25	2.5

walk. The used reference patterns are reported in Table 3 and the corresponding fuzzy membership diagram is given by Fig. 11. The obtained results, showing suitable robot's reaction within both of aforementioned scenarios, are given by Fig. 12. Here as well, the proposed concept defeats the assignment.

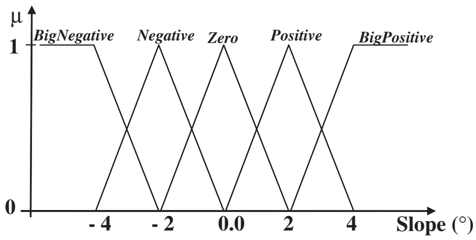
In order to illustrate this intrinsic robustness of the proposed concept, we have evaluated two scenarios: robot's reaction to a ''forward-push force'' and its reaction after a ''backward-push force''. In both scenarios, the above-mentioned perturbations (e.g. forward pushing and backward pushing) affect the robot at $t=15$ s (e.g. after 15 s of regular walking with a desired average velocity of 0:7 m/s). In the first scenario, the trunk of the robot receives an impulsive force during 0.2 s with 50 N m amplitude, resulting on an unexpected increasing of the robot's average velocity as well as on sudden disruption of robot's step length. In the second, the trunk of the robot receives an impulsive force with 25 N m amplitude during the same period (e.g. during 0.2 s), ensuing an unexpected decreasing of the robot's average velocity and an abrupt uproar of its step length. As the obtained results show it (Fig. 13–16), the cognitive artificial abilities, fashioning the robot's reflexive walking, allow the robot to overcome the bewildering impacts of such turbulences. It is pertinent to notice that the any of those turbulences has been learned by the robot and so this appealing ability is a new reflexive ability, which could be seen (interpreted) as cognitive (e.g. knowledge based) self-developed reflexive artificial awareness of our robot. This is a strong, and at the same time, a very attractive issue of the proposed concept).

3.3. Example of CCF: fuzzy-Q-learning CCF for acquiring intentional obstacles' avoidance mind-set

The present sub-section aims to illustrate how the intentional skills may be achieved beside the reflexive walking ability within the frame of the concept introduced in Section 2. We remind that conscious walking relates the robot's ability of walking, interacting with environment issued items (e.g. considering object, obstacles, etc.). As it has previously been assumed, the humanoid robot is supposed to be describable conformably to the Section 3.1. As it has been mentioned in Section 2, a CCF is a constituent of conscious levels (layers) and is associated to premeditated walking performance. As for an unconscious level, a conscious level may include several of such functions. A CCF may also use the skills of other functions (either conscious or unconscious) belonging to the same or to a different cognitive level (in sense of the proposed concept detailed in Section 2). Communications and exchanges are fingered by Inter-Level channel (see Fig. 1). In this case study example, the proposed CCF could be seen as a fuzzy-Q-learning (see [57,59]) function. The goal of the proposed fuzzy-Q-learning based CCF is to find, applying a learning process, a set of fuzzy rules allowing to the biped robot to step-over either a static or a dynamic obstacle. Before focusing the architecture of such FQL based CCF, let us briefly introduce the fuzzy-Q-learning model.

3.3.1. Fuzzy-Q-learning (FQL) concept

Reinforcement learning [53–55] involves problems in which an agent interacts with its environment and estimates consequences of its actions on the base of a ''reinforcement signal'' (a scalar indicator) in terms of reward or punishment. The goal of the reinforcement learning algorithm is to find the action which maximizes the ''reinforcement signal''. The reinforcement signal



• IF Slope is Big-Negative THEN Y = o_1

• IF Slope is Small-Negative THEN Y = o_2

• IF Slope is Zero THEN Y = o_3

• IF Slope is Small-Positive THEN Y = o_4

• IF Slope is Big-Positive THEN Y = o_5

Fig. 11. The fuzzy membership shapes of sloppy-ground reference gait patterns and corresponding linguistic rules.

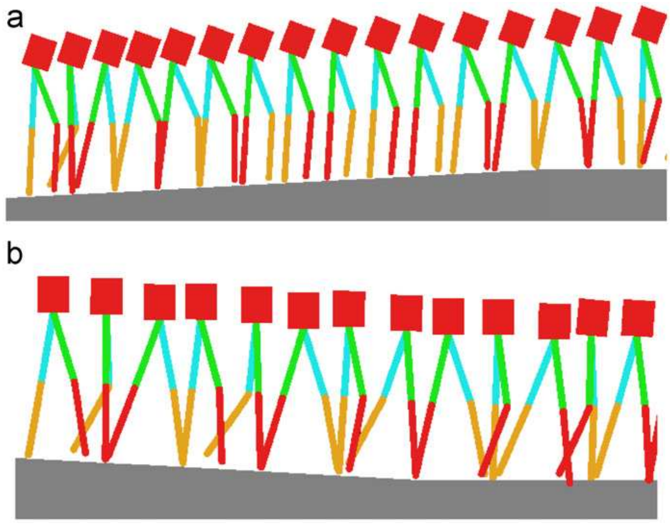


Fig. 12. Stick-diagrams corresponding to the sloppy-ground walk's validation scenarios showing an ascendant walk (a) and a downward walk (b).

provides an indication of the pertinence of last chosen actions. Q-Learning, proposed by Watkins et al. [53], is a very interesting way to use reinforcement learning strategy. However, the Q-Learning algorithm developed by Watkins deals with discrete state space and assumes that values (e.g. Q-matrix) are stored in as a look-up table. So, the use of this method becomes impossible when the state/action space is continuous. For a continuous state space, Glorenec and Jouffe ([56–59]) have proposed fuzzy Q-learning (FQL) concept where both actions and Q-function are represented by Takagi–Sugeno fuzzy inference system (TS-FIS). FQL is an extension of the traditional Q-learning allowing handling the continuous nature of the state-action. Unlike the TS-FIS in which there is only one consequent for each rule, the FQL approach admits several consequences per rule. Therefore, the learning agent has to find the best consequent for each rule where each consequent represents one action. The FQL algorithm uses a set of N_K fuzzy rules such as

$$\text{IF } x_1 \text{ is } M_1^1 \text{ AND } x_2 \text{ is } M_2^1 \ldots \text{ AND } x_i \text{ is } M_i^1$$
$$\text{THEN } \begin{cases} \quad y_k = a_k^1 & \text{with } Q = Q_k^1 \\ \text{or } \; y_k = a_k^m & \text{with } Q = Q_k^m \\ \text{or } \; y_k = a_k^{N_m} & \text{with } Q = Q_k^{N_m} \end{cases}$$

where x_i ($i=1\ldots N_i$) are the inputs of the FIS which represent the state space, N_i is the size of the input space. Each fuzzy set j for the input ith is modeled by a membership function M_i^j and its membership value μ_i^j. a_k^m and Q_k^m are, respectively, the mth possible consequent (action) for the kth rule and its corresponding Q-value ($k=1\ldots N_k$ and $m=1\ldots N_m$). At each step time t, the agent observes the present state (actual state) $X(t)$. For each rule k, the learning system has to choose one action among the total N_m possible actions using an exploration/exploitation policy (EEP). In our approach, ε-greedy algorithm is used to select the local action for each activated rule. This mechanism defines a semi-uniform probability distribution P_ε in which the current best action (e.g. the action with $Max(Q_k^m)$, $m=1\ldots N_m$) is selected with probability $(1-P_\varepsilon)$ and a random action with probability P_ε. After, the execution of the next computed action, the agent may update the Q-value using a reinforcement signal r. The FQL operation may be decomposed into four stages:

- After the fuzzification of the perceived state $X(t)$, the rule values $\alpha_k(t)$ are computed using Eq. (12):

$$\alpha_k(t) = \mu_1^j \mu_2^j \ldots \mu_{N_i}^j \tag{12}$$

- The final action $Y(t)$ is computed through two levels of computation: in the first level, local action l in each activated rule is determined by using EEP, and in the second level global action is calculated as a combination of all local actions. Eqs. (13) and (14) give the global action $Y(t)$ and the corresponding $Q(t)$, respectively:

$$Y(t) = \sum_{k=1}^{N_k} \alpha_k(t) a_k^m(t) \tag{13}$$

$$Q(t) = \sum_{k=1}^{N_k} \alpha_k(t) Q_k^m(t) \tag{14}$$

- Matching up the new action, given by $Y(t)$ and taking into account the environment's reply, $Q(t)$ may be updated using Eq. (15), where $Q_{\max}(t+1)$ (expressed by Eq. (16)) is the maximum Q-value for the activated rule at the next step time (e.g. at $t+1$), γ is a discount factor which can be chosen from 0 to 1. If it is close to 0, the reinforcement information tends to consider only the immediate reward, while whether it is closer to 1, it considers the future rewards with greater weight. β is a learning rate parameter allowing to weight the part of the old and new rewards in the reinforcement signal r:

$$\Delta Q(t) = \beta\left[r + \gamma Q_{\max}(t+1) - Q(t)\right] \tag{15}$$

$$Q_{\max}(t+1) = \sum_{k=1}^{N_k} \alpha_k(t+1) \mathrm{Max}\left[Q_k^m(t+1)\right] \tag{16}$$

- Finally, for each activated rules, the corresponding elementary quality ΔQ_k^m of the Q-matrix is updated conformably to Eq. (17).

$$\Delta Q_k^m = Q(t)\alpha_k(t) \tag{17}$$

3.3.2. Architecture of fuzzy-Q-learning conscious cognitive function developing "obstacles' avoidance" ability

The proposed fuzzy-Q-learning (FQL) CCF comprises three AEC (performing elementary actions): one of them is a Takagi–Sugeno fuzzy inference system (TS-FIS), the other is a reinforcement signal manager and the third one is a gait patterns simulator. The DEC is a reinforcement learning [53] (Q-learning [54,55]) based rules' overseer (assessor). The exteroceptive information (interaction with environment) is related to the obstacle: distance between

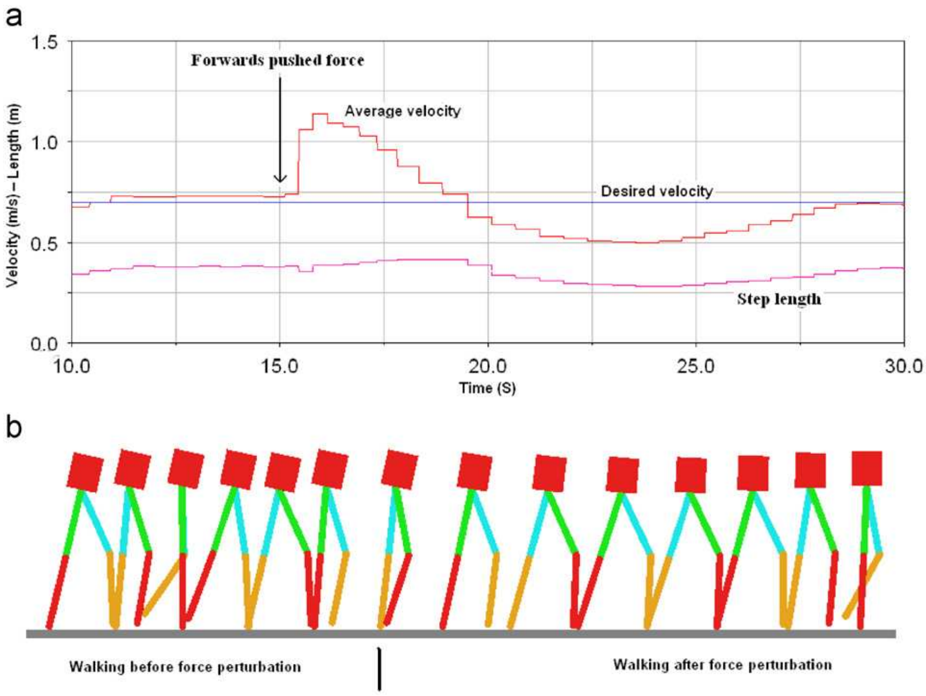


Fig. 13. Waveforms representing the desired average velocity, robot's average velocity and generated length steps (a) and stick-diagram (b) corresponding to the robot's reaction to a ''forward-push force''.

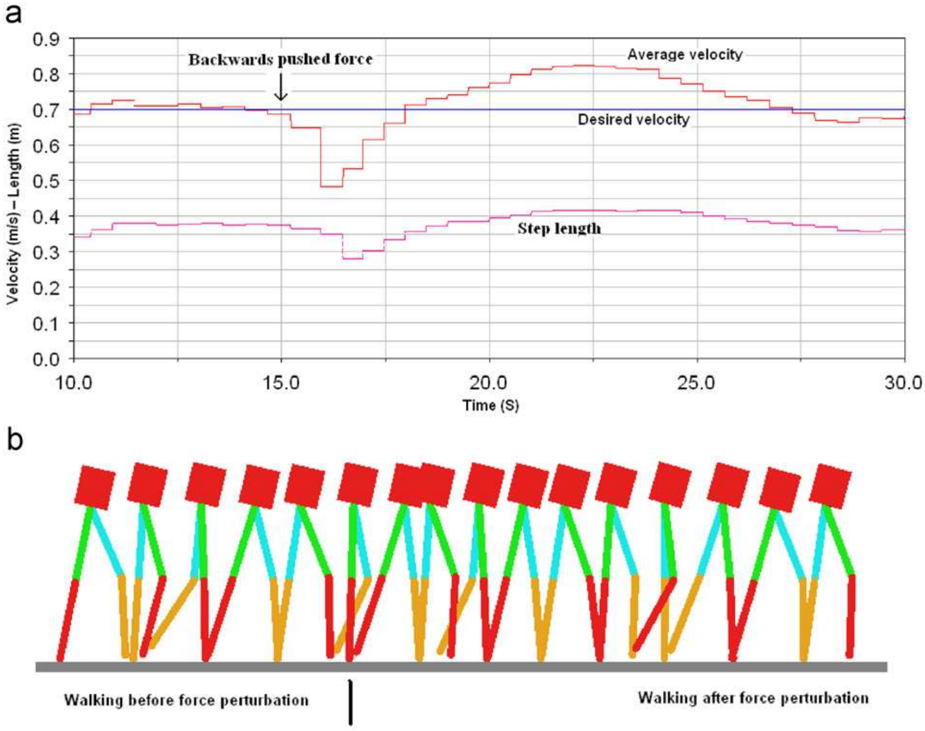


Fig. 14. Waveforms representing the desired average velocity, robot's average velocity and generated length steps (a) and stick-diagram (b) corresponding to the robot's reaction to a ''backward-push force''.

the robot and the obstacle (d_{obs}) and the obstacle's relative velocity (V_{obs}). Fig. 15 depicts the proposed FQL based CCF. As this figure shows and taking into account the involved exteroceptive information, the input of CCF is $\Psi_k=(d_{obs}, V_{obs})$. If the obstacle is static then $V_{obs}=0$. The output information of the CCF is the proposed (appropriated) average velocity, which is suitable to generate a gait pattern allowing stepping over the obstacle. Thus, such CCF will communicate its output result to unconscious level (e.g. as ''desired'' average velocity V_M^d) resulting on a suitable control of the ''flat-ground'' walking of the biped robot.

The role of gait patterns' simulator AEC is to generate different values corresponding to possible (L_{step}, t_{step}) and issued average velocity (computed accordingly to Eq. (3)). The fuzzification AEC is a TS-FIS determining $\alpha_k(t)$ conformably to what has been

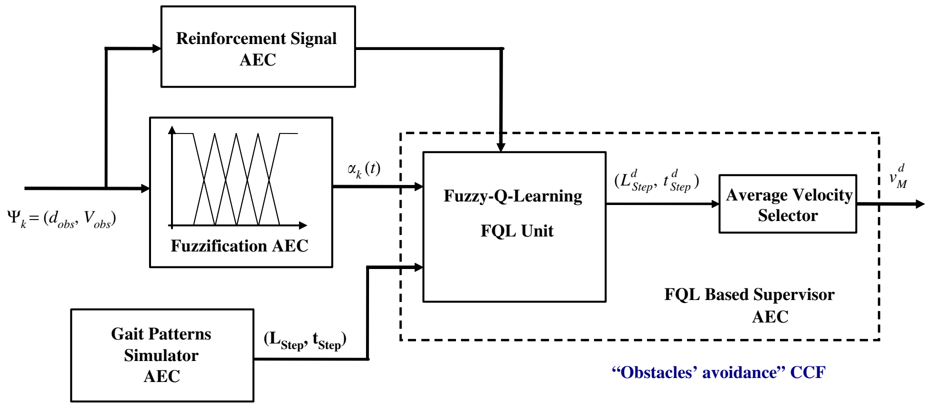


Fig. 15. General bloc diagram of the ''obstacles' avoidance'' CCF.

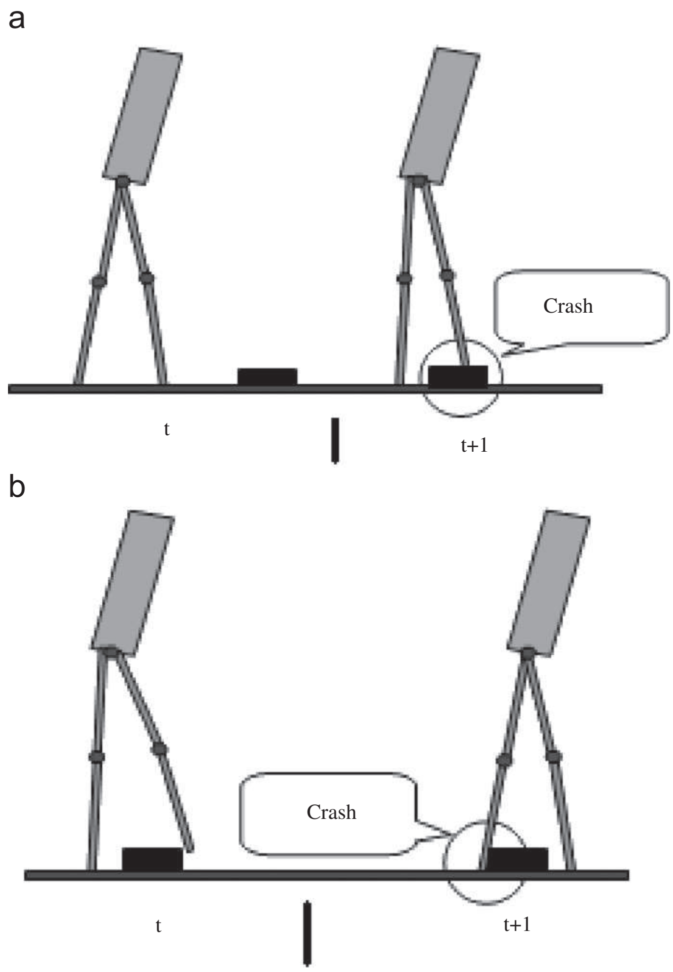


Fig. 16. Crashes configurations into a dynamic obstacle. The swing leg touché directly the obstacle (a) and the obstacle comes to touch with the stance leg (b).

mentioned in Section 3.3.1. The reinforcement signal manager AEC handles the scalar indicator specific to Q-Learning approach (reward or punishment value), informing the learning process (the learning agent) about the quality of the chosen action. Concerning the ''obstacle's stepping over'' action, we have designed reinforcement signal in three parts:

- $r = 0$, when the robot is in front of the obstacle,
- $r > 0$, if the robot steps over the obstacle,
- $r < 0$, if the robot crashes into the obstacle.

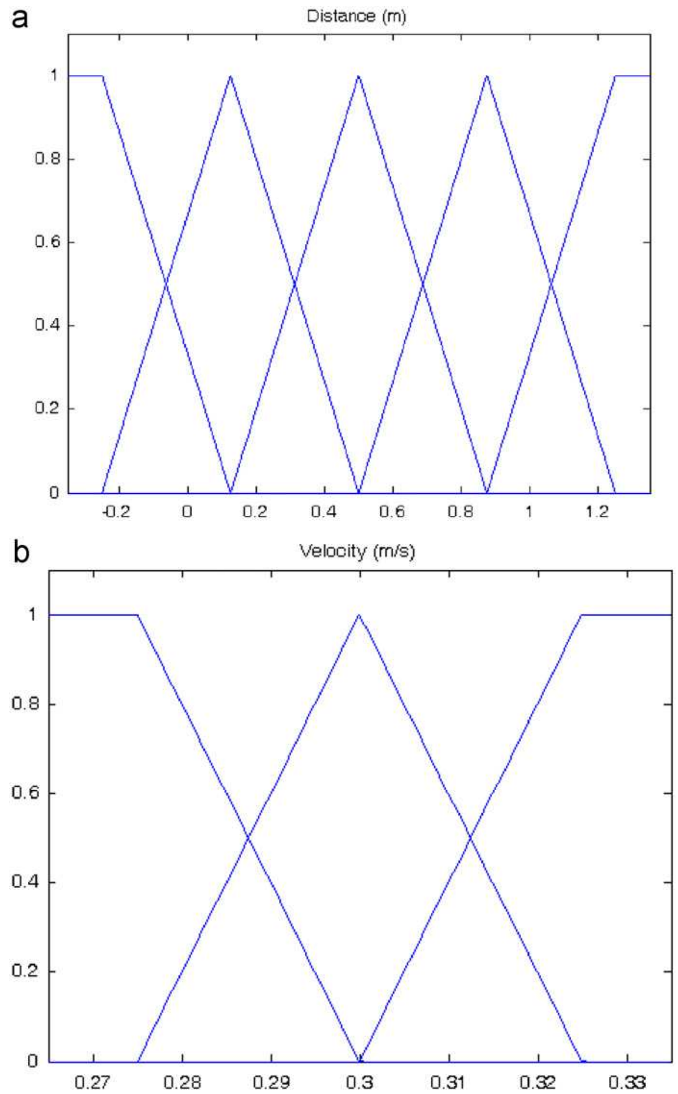


Fig. 17. Membership functions defined for the input space. Obstacle distance is measured in m (a) and obstacle's velocity in m/s (b).

Finally, the FQL based DEC includes two modules. The first one is a FQL unit determining the most appropriated step's length (L^d_{step}) and the corresponding step's length duration (t^d_{step}). It operates conformably to what has been stated in 3.3.1. The second stage computes the computes the average velocity corresponding to that most appropriated step's length (e.g. computing V_M^d: the output of the CCF).

3.3.3. Validation results

The validation has been performed considering the same real biped robot used in previous section (with features given by Table 1). The validation has been performed according to the following statements: the robot has the ability to adjust its steps (length and duration). Consequently, there are two possibilities in which the robot may crash with the obstacle. Fig. 16 shows these two possibilities. First one occurs when the length of the step is not correctly adapted according to the position of the dynamic obstacle. In this case, the swing leg touches directly the obstacle during a double support phase (Fig. 16a). The other case corresponds to the situation where the obstacle comes to touch the stance leg during the single or double support phase (Fig. 16b). If the obstacle is static then the second possibility is escaped (e.g. doesn't occur).

We consider that the walking of the biped robot may include as well strings of single support phases (only one leg is in contact with the ground) as instantaneous double support phases (the two legs are in contact with the ground). The biped robot may adjust the both length and duration of its steps. The size of the obstacle is constant but the velocity of the obstacle may be modified around a medium value which represents an average velocity. In fact, the obstacle velocity is a sum of the average velocity and a random

Table 4
Reference gait generated for "obstacle-avoidance" validation scenario.

Reference gait	L_{step} (m)	t_{step} (s)	V_M^d (m/s)
Gait[1]	0.24	0.6	0.4
Gait[2]	0.30	0.6	0.5
Gait[3]	0.34	0.567	0.6
Gait[4]	0.38	0.543	0.7
Gait [5]	0.43	0.537	0.8

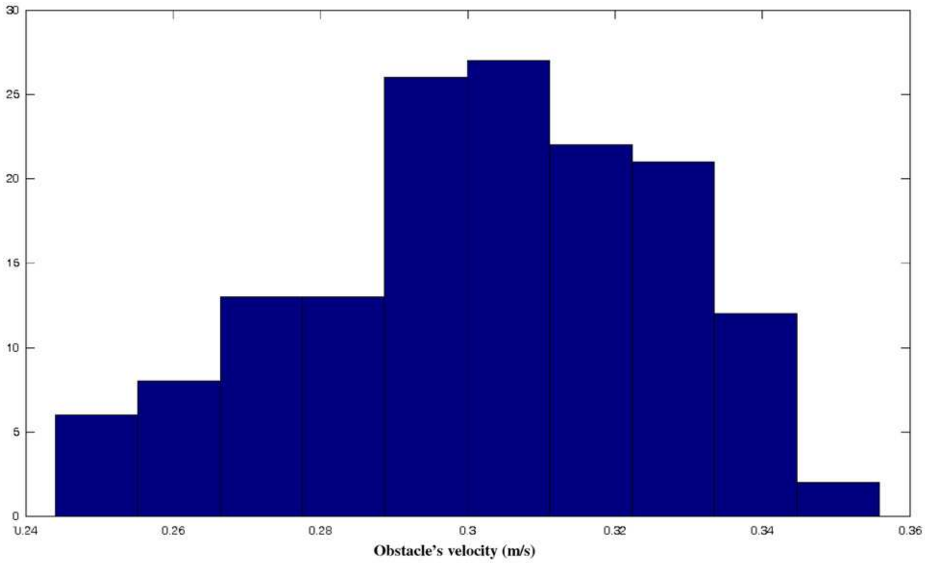


Fig. 18. Repartition of the chosen values of the obstacle's velocity (V_{obs} is measured in m/s) during the training phase.

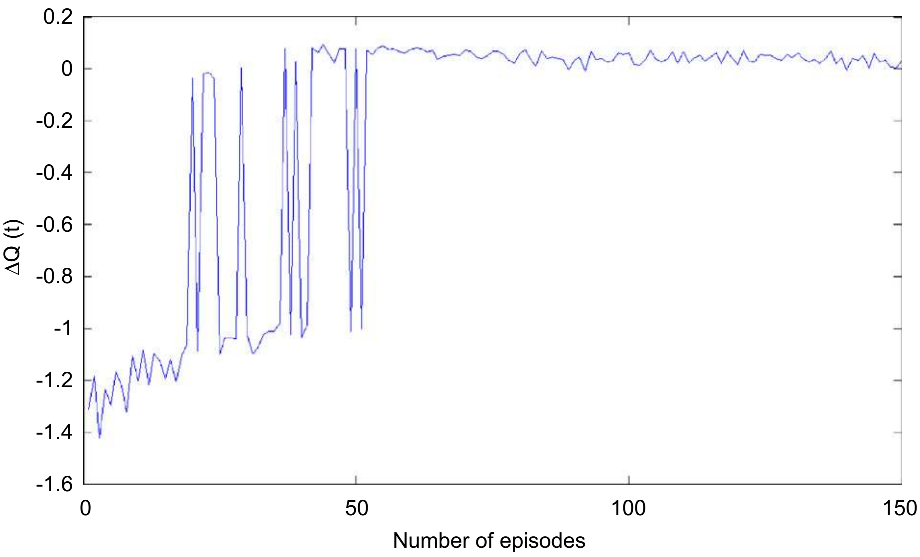


Fig. 19. Evolution of $\Delta Q(t)$ (Q-value) during the learning phase.

value with a Gaussian probability. d_{obs} is considered as the distance between the front foot and the first side of the obstacle. d_{obs}, and V_{obs} are updated at each double support phase. During the learning, we use what we define as "episodes". An "episode" is an elementary scenario where the biped robot moves step by step towards the obstacle (static or dynamic) with a given average velocity V_M. If the obstacle is a dynamic one then the episode's information comprise the robot's average velocity (V_M), the obstacles velocity (V_{obs}) and the distance between the robot and the obstacle (d_{obs}). This information is reduced to V_M and d_{obs} when the obstacle remains static (e.g. $V_{obs}=0$ during such episode). An episode is finished whether the robot steps over the obstacle (success) or if the robot crashes into obstacle (failure). As it has been previously mentioned, during this training stage, the goal of the FQL based learning process is to find the best consequent for each rule, where each consequent represents one action. The probability distribution P_ε is given by Eq. (18) where N_{epi} is the number of episodes. This means that the random exploration is privileged at the beginning of the learning. In other words, P_ε strongly decreases when the number of episodes increases:

$$P_\varepsilon = \frac{1}{10+N_{epi}^2} \tag{18}$$

The input space (e.g. $\Psi_k=(d_{obs}, V_{obs})$) membership functions have been defined accordingly to Fig. 17. The generated reference gaits are given in Table 4.

On the base of the previous description, the Q-matrix has been trained during 150 episodes. One episode is finished when the robot crash into obstacle or when the robot steps over the obstacle. During the learning phase, at each episode:

- the velocity is chosen in random manner (Gaussian probability $\sigma=0.02$) around the median value 0.3 m/s (see Fig. 18).
- the initial distance between the robot and the obstacle is around 2.5 m (i.e. the median value of 2.5 m plus a random value).

Fig. 19 shows the sum of the evolution of the Q-value (e.g. $\Delta Q(t)$) during the learning. It must be noticed that this value, which depends directly of the reinforcement signal, converges toward 0 quickly (after 60 learning episodes). The obtained best rules (corresponding to highest magnitudes of Q-values) are then obtained. Table 5 gives an example of the found best rules in the case of an obstacle of 0.1 m size moving with a velocity $V_{obs}=$ 0.3 m/s). Fig. 20 shows results obtained for a dynamic obstacle (obstacle size is 0.1 m) moving at 0.3 m/s. It shows the successful stepping over of the dynamic obstacle. As one can see from this figure, at the beginning robot is walking toward the obstacle with a 0.8 m/s average velocity. The obstacle moves toward the robot with 0.3 m/s velocity. During its walking sequence (five steps), the robot adapts its successive lengths (see Fig. 20b), its successive steps' durations (see Fig. 20d) and its average velocity (see Fig. 20c) in order to ensure a successful stepping over of the obstacle. In fact, this is a plenty intentional walking mode of the robot. Fig. 21 gives stick-diagrams relatives to two cases: the first one (Fig. 21a) corresponds to the situation where the robot is walking in a reflexive way, escaping exteroceptive information (e.g. doesn't interacts with the environment); the second one corresponds to the above-described intentional obstacle avoiding walking sequence example.

Finally, Figs. 22 and 23 show the stick-diagram chain and the length step's string of robot's walking, corresponding to last 15 s of a 25 s walking sequence, where it avoids an obstacle (obstacle size is 0.2 m). Fig. 23 plots also, on the same diagram, the robot's length step's string when the robot performs the same sequence without encountering obstacles. One can remark that without obstacle, the length of the step depends only to the robot's average velocity. Consequently, L_{step} is quasi-constant during the walking. But if an obstacle occurs, the conscious cognitive walking ability of the robot allows the robot to steps over the obstacle, by adjusting its step

Table 5
Example of best rules found after the learning phase when the obstacle size is 0.1 m and $V_{obs}=0.3$ m/s.

$V_{obs} d_{obs}$	Small	Medium	Big
Very-Small	**Gait^3**	Gait^3	Gait^3
Small	**Gait^5**	Gait^4	Gait^1
Medium	**Gait^5**	Gait^2	Gait^1
Big	**Gait^3**	Gait^3	Gait^3
Very-Big	**Gait^5**	Gait^5	Gait^5

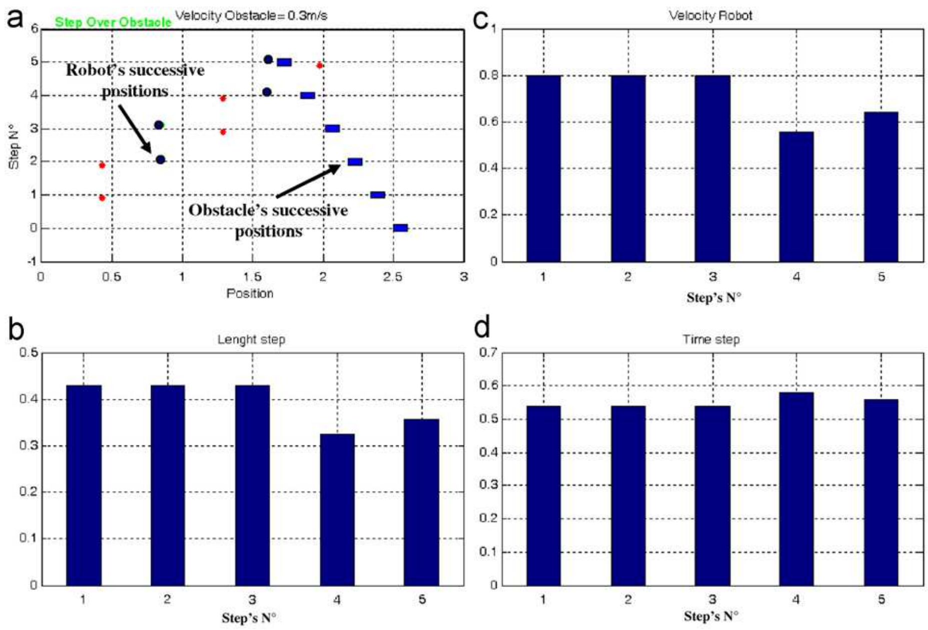


Fig. 20. Example of successful stepping over of a dynamic obstacle (obstacle size is 0.1 m) moving at 0.3 m/s. Successive positions of robot and the obstacle (a). Successive robot's step lengths (b). Successive robot's average velocities (c). Successive robot's step's durations (d).

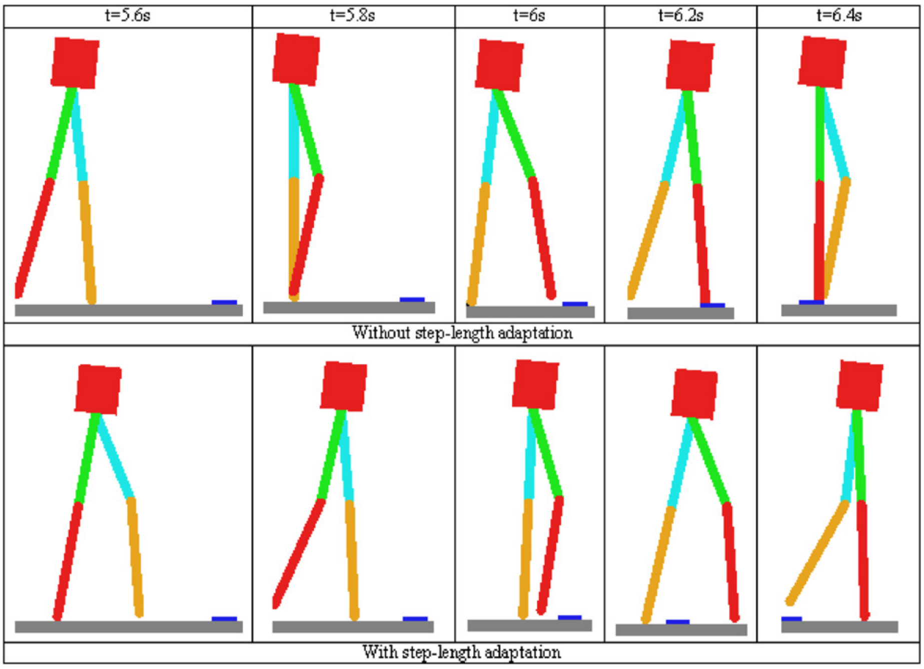


Fig. 21. Stick-diagrams relatives to the robot's reflexive walking (upper) and robot's intentional walking (lower).

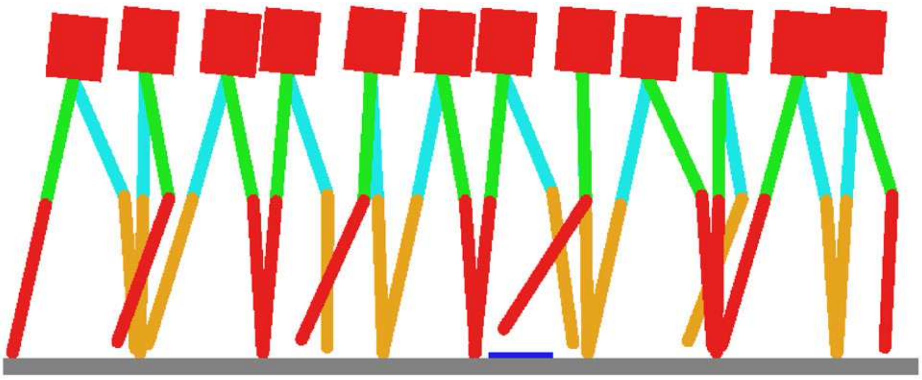


Fig. 22. Stick-diagram of robot's intentional walking avoiding an obstacle.

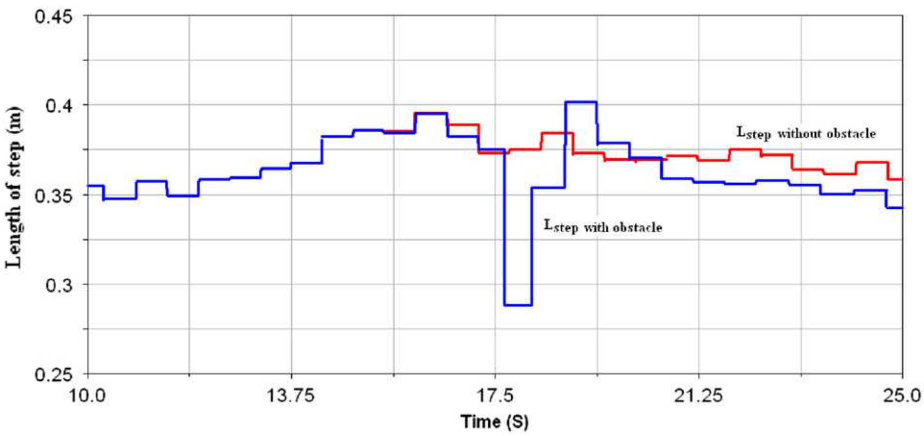


Fig. 23. Length step's string of robot's walking with obstacle corresponding to the walking sequence shown in Fig. 22 and comparison of this length step's string with the case where any obstacle comes across.

lengths. In this case, the step length is adjusted (robot strongly decreases its step's length) in order to match up the robot's swing leg's landing point (landing position) just before the obstacle. The next step, the step length increases allowing to the robot to step over the obstacle.

4. Conclusion

By supplanting the problem of humanoid robots' artificial walking from the "control theory" backdrop to the "cognitive machine learning" backcloth, the proposed multi-level cognitive machine-learning based concept attempts to offer a unified model of human-like artificial biped walking process, slotting in two kinds of cognitive levels: "unconscious" and "conscious" cognitive levels, answerable of reflexive and intentional processed of biped walking, respectively. The first key-advantage of conceptualizing the problem within such incline is to detach the build-up of artificial biped walking from the type of robot. The second chief-benefit of the concept is that the issued structure is "machine learning" based foundation taking advantage from "learning" capacity and "generalization" propensity of such models.

The validation has been performed considering attributes of a real biped robot, showing effectiveness of the proposed cognitive multi-level architecture. On the side of reflexive walking ability, the studied examples and the designed neuro-fuzzy (fuzzy-CMAC) based UCF show two strong, and at the same time, very attractive issues of the proposed concept. The first, relating its universality, means that different reflexive walking aptitudes are achievable using the same structure (same UCF). The second, relating the robustness, consists on self-development of new reflexive skills which could be seen as some kind of artificial cognitive awareness of the walking robot. On the side of intentional walking aptitudes, the dynamic obstacles avoidance case study and the designed FQL based CCF demonstrated the pertinence of the proposed concept for construction of high-level cognitive tasks.

The presented work opens a number of promising perspectives. One of those promising directions on which we continue to advance is building additional (various) reflexive cognitive functions surrounding another basic walking intuitions (as the walking of bumpy (irregular) ground). Another propitious direction in which we are engaged is designing new intentional functions and levels relating visual interaction with environment and semantic gait planning. This second trend of the above-described multi-level cognitive concept is essential to acquire humanoid robots' autonomy (e.g. to reach the robot's autonomous walking in an unknown environments). Finally, the last encouraging direction in which we put our effort is the extension (application) of the proposed cognitive concept to other robotics paradigms, such as collective or social robots.

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A machine learning based intelligent vision system for autonomous object detection and recognition

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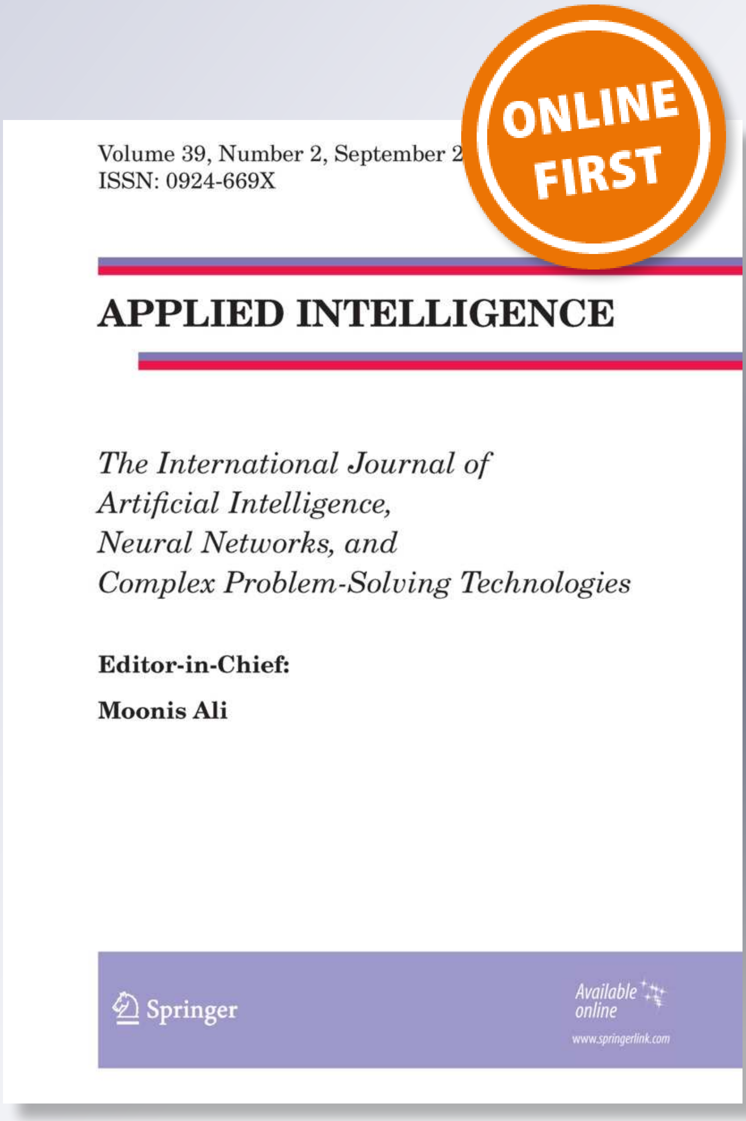
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A machine learning based intelligent vision system for autonomous object detection and recognition

Dominik Maximilián Ramík · Christophe Sabourin · Ramon Moreno · Kurosh Madani

Abstract Existing object recognition techniques often rely on human labeled data conducting to severe limitations to design a fully autonomous machine vision system. In this work, we present an intelligent machine vision system able to learn autonomously individual objects present in real environment. This system relies on salient object detection. In its design, we were inspired by early processing stages of human visual system. In this context we suggest a novel fast algorithm for visually salient object detection, robust to real-world illumination conditions. Then we use it to extract salient objects which can be efficiently used for training the machine learning-based object detection and recognition unit of the proposed system. We provide results of our salient object detection algorithm on MSRA Salient Object Database benchmark comparing its quality with other state-of-the-art approaches. The proposed system has been implemented on a humanoid robot, increasing its autonomy in learning and interaction with humans. We report and discuss the obtained results, validating the proposed concepts.

Keywords Intelligent machine vision · Visual saliency · Unsupervised learning · Object recognition

1 Introduction

The design of perceptual functions is a major problem in robotics. Fully autonomous robots need perception to navigate in space and recognize objects and environment in which they evolve. But the question of how humans learn, represent, and recognize objects under a wide variety of viewing conditions presents a great challenge to both neurophysiology and cognitive research, and of course, in the robotics field [9]. This paper focuses on a fundamental skill in artificial intelligence applied to robots evolving in a human environment, which are the learning and recognition process based on visual perception.

In the past decade, the scientific community has witnessed great advance on the field of techniques for object detection and recognition, such as SIFT [22], SURF [7], Viola-Jones framework [34], to mention only a few. More recently, in [16] Hossain et al. proposed "knowledge-based flexible-edge-matching" method to detect moving object detection in video sequences. Some works, also, have focused on feature selection and feature extraction like in [19]. Other works focused on cognitive approaches, as in [35], where authors have proposed to use a memory-based cognitive modeling for robust object extraction and tracking. Many of them were so successful, that we are already meeting them in commercial applications like cameras focusing automatically on human faces or product logo recognition in mobile applications. While these methods show often high rates of recognition and are able to operate in real time, they all rely on a human made databases of manually segmented or labeled images containing the object of interest without extensive spurious information and background. There are many

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advanced works applying the mentioned approaches to enable learning and recognition in mobile robots, e.g. the Curious George robot described in [23], or [3] who use SIFT in context of a robust neural network based object recognition framework. Some of the techniques use such a database as learning samples to train a set of classifiers [34], others use it as a bank of templates for matching processes [6, 7]. The mentioned database is sine qua non for a successful recognition process, but its manual creation often requires a considerable time and a skilled human expert. This impedes design of a fully autonomous machine vision system, which would learn to recognize new objects on its own.

Motivated by the mentioned shortcomings regarding existing as well object recognition methods as vision systems, we present in this work an intelligent machine learning based system able to observe and learn autonomously individual objects present in a real environment. The goal for this system is to allow an embodied agent (e.g. a camera equipped mobile robot) to learn and to recognize objects encountered in its environment in completely autonomous manner. This addresses a foremost problem relating to autonomous robots' area, as in a more generic way autonomous artificial vision paradigm. It appears also as vital for reaching higher-level intelligent machines: machines able to "discover" and to learn unknown (e.g. not formerly memorized or stumbled upon) object from an unlabeled image. A clear need appearing as a first expected skill is the ability to select from the overwhelming sensory information (e.g. visual information) only the pertinent ones. Then, additional manifest needs are visual knowledge acquisition (learning the pertinent visual information) and already encountered objects' recognition (namely, based of acquired knowledge).

In design of such a system, our approach has been inspired partly by existing clinical investigations describing human vision system and partly by the way human learns objects. In fact, the extraction of objects of interest from raw images is driven by visual saliency. Building on existing work relating the field of visual saliency, we propose an intelligent vision system (concept, architecture and implementation on real robot) taking advantage from a novel salient objects' detection algorithm. Our choice to consider a spherical interpretation of RGB color space allows the system to take advantage from photometric invariants. This conducts to a fast image segmentation algorithm, robust to real-world illumination conditions, which serves to extract objects for learning from raw images. Resulting extracted objects can be then learned by most of the up to date machine-learning approaches in order to ease their recognition if they would be encountered afterwards. Concerning the implementation, two well known machine-learning based fast recognition methods have been tested: Speeded-up Robust Features (SURF) introduced in [6] and the Viola-Jones object detection framework, presented in [34]. Finally we validate our artificial cognitive system with an embedded color camera on a mobile robot in an explore-and-learn task performed in a common office environment.

The reminder of the work is organized as follows. Section 2, after a short overview of existing techniques about visual saliency, presents constitutive parts of our system and explains their interaction. In Sect. 3, we present our approach to saliency detection. In Sect. 4, we detail our salient object extraction technique. Learning procedures are detailed in Sect. 5. The Sect. 6 reports and discusses results of validation of the proposed intelligent vision system. Conclusion and further work perspectives are presented in Sect. 7.

2 Autonomous object detection and recognition based on visual saliency

In recent years, there has been a substantial progress in robotic systems able to robustly recognize objects in real world using a large database of pre-collected knowledge (see for example [3, 23]). But a fully autonomous robot cannot rely solely on a priori knowledge that has been given to it by a human expert. On the contrary, it should be able to learn on-line, in the place where it is used. If we want to allow a machine vision system to learn how to recognize an unknown object from an unlabeled image, we are in a similar situation as human parents teaching an infant. A clear need, for human and for machine as well, is from the overwhelming flow of sensory information to choose only the one which is pertinent in context of the given task. This is why, in our artificial visual cognitive system, the extraction of objects of interest from raw images is driven by visual saliency. Then, the resulting extracted objects can be exploited by existing recognition methods like SURF or Viola-Jones in our case. It is the ability of calculation of visual saliency, that enables our system to extract and learn individual objects and thus it is the cornerstone of our system. For this reason we will dedicate the following Sect. 2.1 to remind existing techniques about visual saliency. After this remember, Sect. 2.2 describes an overview of our cognitive system for visual perception.

2.1 Existing techniques about visual saliency

It may be generalized, that it is the saliency (in terms of motion, sound, color, etc.) that makes the pertinent information to be remarked or to "stand-out" from the context. For our purposes, we identify the mentioned explicitness with visual saliency. We argue that presenting an object in an explicit way, i.e. that it becomes visually distinct with respect to the rest of the scene may enable unsupervised extraction of such an object from the perceived image so that it can be used as a learning example for an object detector. We show further on (see Sect. 6 for our experimental setup and images) that this explicitness does not necessitate an artificial scene setup (e.g. putting the learned object on a white background) but, on the contrary, that our system is able to learn objects presented in natural indoor conditions without any particular scene arrangement. This point is very important in the design of a fully autonomous vision system able to learn and recognize salient objects in a real environment.

Visual saliency (also referred in literature as visual attention, unpredictability or surprise) is described as a perceptual quality that makes a region of image stand out relative to its surroundings and to capture attention of the observer [2]. The inspiration for the concept of visual saliency comes from the functioning of early processing stages of the human vision system and is roughly based on previous clinical research. In early stages of the visual stimulus processing, human vision system first focuses in an unconscious, bottom-up manner, on visually attractive regions of the perceived image. The visual attractiveness may encompass features like intensity, contrast and motion. Although there exist solely biologically based approaches to visual saliency computation, most of the existing works do not claim to be biologically plausible. Instead, they use purely computational techniques to achieve their goal. One of the first works to use visual saliency in image processing has been published by [18]. Authors use an approach based on a center-surround contrast calculation using Difference of Gaussians. Other common techniques of visual saliency calculation published more recently include graph-based random walk [15], center-surround feature distances [1], multiscale contrast, center-surround histogram and color spatial distribution [21] or features of color and luminance [2]. A less common approach is described in [20]. It uses content-sensitive hypergraph representation and partitioning instead of using more traditional fixed features and parameters for all images.

In image processing, identification of visually salient regions of an image are used in numerous areas including smart image resizing [5], adaptive image display on small device screens [10], amelioration of object detection and recognition [28], content based image retrieval and adaptive image compression or image collection browsing to mention only a few. Depending on the particular technique, many approaches like [1, 2] or [21] output the saliency map, which is an image whose pixel intensities correlate with the saliency of the corresponding pixels of the original image. Selection of the most salient regions from saliency map by application of a threshold or a segmentation algorithm is subsequently performed. It results into extraction of a visually important object or a patch of objects rather than just of a semantically incoherent fragment of the image. This property is exploited by several authors. In [8] a biologically-motivated saliency detector is used along with an unsupervised grouping algorithm to group together images containing visually similar objects. Notably in the work [31] a purely bottom-up system based on visual attention is presented, investigating the feasibility of unsupervised learning of objects from unlabeled images. Experiments are successfully conducted by its authors on real world high-resolution still images and on a camera-equipped mobile robot, where the capacity to learn landmark objects during its navigation in an indoor environment is shown. The main difference between this approach and the our one is, that Rutishauser et al. use visual saliency rather to indicate interesting parts of the input image, while we use it explicitly for extraction of individual visually important objects. Recently [12] has used a real-time method for salient object tracking on a mobile robotic platform. However, objects are learned here in a supervised manner with assistance of the operator.

Object of interest extraction is driven by its saliency, therefore accurate and fast salient region detection is crucial for our system. Although there exist numerous approaches described in the literature, not all of them are suitable for our purposes. Often they lack precision or good resolution in frequency domain, are only able to extract the one most salient object from the image, or are computationally too heavy to be used in real-time. A comparison of some state-of-the-art algorithms in these terms may be found in [2]. In this work, we propose a novel visual saliency allows to design a fast image segmentation algorithm, robust to real-world illumination conditions allowing to extract several objects from raw images. The visual saliency is used in the first part of our system. But before describing in detail the visual saliency in Sect. 3, we begin to give an overview of the system in the following sub-section.

2.2 System overview

The system we propose here consists of several units which collaborate together on the goal. On Fig. 1 a block-diagram of the system is depicted showing the individual units and their relations. Two main parts may be identified. The first one, labeled "Acquisition of new objects for learning" takes a raw image from the camera, detects visually important objects on it and extracts them so that they can be used as prospective samples for learning. These samples are then used in the second part ("Learning and recognition"), where learning of the extracted objects is done and thus further recognition of those objects is made possible.

Each one of the two mentioned parts contains several processing units. In the first unit, as a new image is acquired by the camera, it is processed by the "Salient region detection" unit (described in Sect. 3). Here, using hybrid features of chromaticity and luminosity along with local features of center-surround histogram calculation, a saliency map is constructed. It highlights regions of the image that are visually important, i.e. that are visually more salient with respect

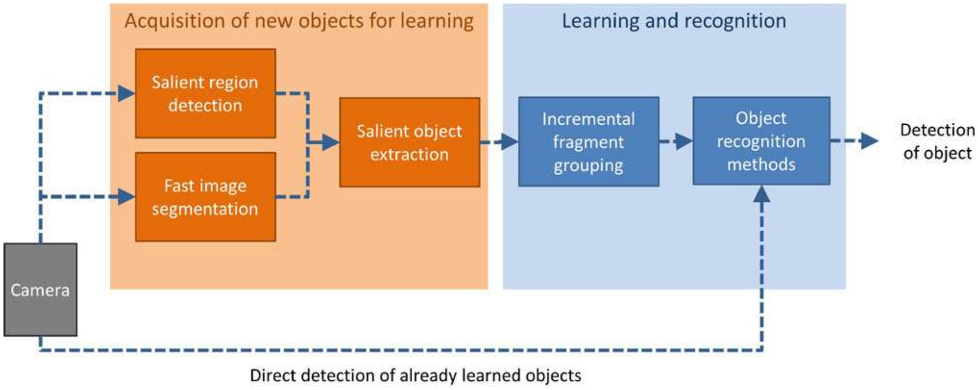

Fig. 1 Block diagram of our system and it's units

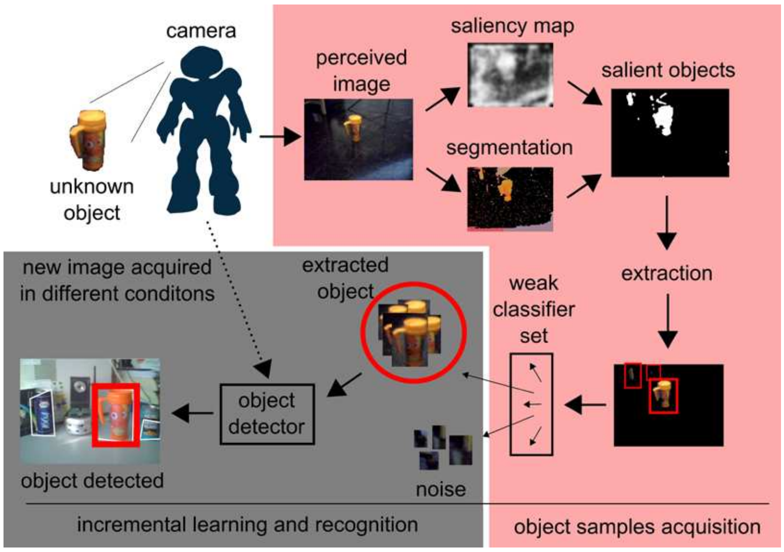

Fig. 2 Overview of the entire proposed system's work-flow. An unknown object is incrementally learned by extracting it and providing it as learning samples to the object detector (*solid arrows*). This enables recognition the object when encountered again (*the dotted arrow*)

to the rest of the image. In parallel the input image is processed in the "Fast image segmentation" unit, which splits the image into a set of segments according to the chromatic surface properties. The algorithm is shown to be robust to common illumination effects like shadows and reflections, which helps our system to cope with real illumination conditions. Finally the "Salient object extraction" unit (Sect. 4) combines results of the two previous, extracting the segments found on regions that exhibit significant saliency and forming them together to present at the end salient objects extracted from the input image.

As images are taken consecutively by the camera, salient objects extracted from each one are fed into the "Incremental fragment grouping" unit (Sect. 5). Here, an on-line classification is performed on each object by a set of weak classifiers and incrementally groups containing the same object extracted from different images are formed. These groups can be then used as a kind of visual memory of visual database describing each of the extracted objects. This alone could be enough for recognition of each of the objects, if it was ensured that each particular object will be found in the same visual context (i.e. in the context where the object is salient with respect to its surroundings) next time it is encountered by our system. This is clearly too restrictive for a system with a goal to recognize the once learned objects in any condition. That is why we add the last unit of our system, tagged "Object recognition methods". Its role is, by employing existing object recognition algorithms, to learn from the visual database build by "incremental fragment grouping" unit and to recognize those objects regardless to their saliency in new settings. Thus for once learned objects, they can be recognized directly on the input image, which is denoted by the very bottom arrow on the Fig. 1 labeled "Direct detection of already learned objects".

A different view on our system is presented on Fig. 2, where its work-flow is visualized. In short, based on the previous description, we can argue that the proposed cognitive system allows to design an artificial visual system with the following key capacities:

– autonomous extraction of salient objects from raw unlabeled camera images,
– learning of those objects and further recognition of the learned objects,

- robustness in order to recognize the learned objects in different conditions or visual contexts,
- embedded system and real time computing for robotic applications.

The next section describes, in detail, the new salient object detection algorithm which is used in this work.

3 Salient region detection

In this section, we propose a novel visual saliency detector composed of two independent parts, which can be computed in parallel. The first part captures saliency in terms of hybrid distribution of colors (i.e. a global saliency characteristic, Sect. 3.2). The second part calculates local characteristics of the image using a center-surround operation (Sect. 3.3). Their resulting saliency maps are merged together using a translation function, resulting in the final saliency map (Sect. 3.4).

In the proposed saliency computation algorithm, we are representing colors using a spherical interpretation of RGB color space (siRGB further on). This allows us to work with photometric invariants instead of pure RGB information. In this section, we begin to remember the main principles of siRGB (Sect. 3.1) but there are several works that explain in detail the siRGB color space and photometric invariants, see [25] and [33].

3.1 A spherical interpretation of RGB color space

Any image pixel's color corresponds to a point in the RGB color space $\{R_c, G_c, B_c\}$. The vector going from the origin up to this point can be represented using spherical coordinates $c = \{\theta_c, \phi_c, l_c\}$, where θ is zenithal angle, ϕ is azimuthal angle and l is the vector's magnitude (intensity). In RGB color space, chromaticity Ψ_c of a color point is represented by its normalized coordinates $r_c = \frac{R_c}{R_c+G_c+B_c}$, $g_c = \frac{G_c}{R_c+G_c+B_c}$, $b_c = \frac{B_c}{R_c+G_c+B_c}$, such that $r_c + g_c + b_c = 1$. That is, chromaticity corresponds to the projection on the chromatic plane Π_Ψ, defined by the collection of vertices of RGB cube $\{(1,0,0), (0,1,0), (0,0,1)\}$, along the line defined as $L_c = \{y = k \cdot \Psi_c; k \in \mathbb{R}\}$. In other words, all the points in line L_c have the same chromaticity Ψ_c, which is a 2D representation equivalent to one provided by the zenithal and azimuthal angle components of the spherical coordinate representation of the color point. Given an image $\Omega(x) = \{(R, G, B)_x; x \in \mathbb{N}^2\}$, where x refers to the pixel coordinates in the image grid domain, we denote the corresponding spherical representation as $\Omega(x) = \{(\theta, \phi, l)_x; x \in \mathbb{N}^2\}$, which allows us to use $(\theta, \phi)_x$ as the chromaticity representation of the pixel's color. For computational purposes, further on we normalize the angle θ and ϕ and the value l into a range from 0 to 255.

3.2 Global saliency features

For the first part, calculation of color saliency is done using two features: the intensity saliency (1) and the chromatic saliency (2). Here we define the saliency as Euclidean distance of intensity l (or azimuth ϕ and zenith θ respectively) of each pixel to the mean of the entire image. Index l stands for intensity channel of the image, $\Omega_{\mu l}$ is the average intensity of the channel, similarly for azimuth ϕ and zenith θ in (2). The term (x) denotes coordinates of a given pixel on the image.

$$M_l(x) = \left\| \Omega_{\mu l} - \Omega_l(x) \right\| \tag{1}$$

$$M_{\phi\theta}(x) = \sqrt{\left(\Omega_{\mu\phi} - \Omega_\phi(x)\right)^2 + \left(\Omega_{\mu\theta} - \Omega_\theta(x)\right)^2} \tag{2}$$

The composite color saliency map M is a hybrid result of combination of maps resulted from (1) and (2). Blending of the two saliency maps together is driven by a function of color saturation of each pixel. For this purpose, we define the color saturation C_c. It is calculated from RGB color model for each pixel as pseudo-norm given by $C_c = \max[R, G, B] - \min[R, G, B]$. When C_c is low (too dark or too bright areas of the image), more importance is given to intensity saliency (1). When C_c is high (vivid colors), chromatic saliency (2) is emphasized. As blending function we use the logistic sigmoid, so that the composite saliency map M is calculated following (3) where $C = 10(C_c - 0.5)$.

$$M(x) = \frac{1}{1 - e^{-C}} M_{\phi\theta}(x) + \left(1 - \frac{1}{1 + e^{-C}}\right) M_l(x) \tag{3}$$

Similar feature as we compute in (1) is used by [2]. However its authors use only a single distance for all three channels, mixing chromaticity and intensity value of pixels together, while our approach respects the color saturation, which allows us to treat separately chromatic and achromatic regions. This is particularly helpful in cases where both chromatic and achromatic objects are present on the image.

3.3 Local saliency features

For the local saliency features, the idea is to go through the entire image and to compare the content of a sliding window with its surroundings to determine, how similar the two are. If similarity is low, it may be a sign of a salient region. Let us have a sliding window P of size p, centered over pixel (x). Define a (center) histogram H_c of pixel intensities inside it. Then let us define a (surround) histogram H_s as histogram of intensities in a window Q surrounding P in a manner that the area of $(Q–P) = p^2$. The center-surround feature d is then given as over all histogram bins (i).

$$d(x) = \sum_i \left| \frac{H_c(i)}{H_c} - \frac{H_S(i)}{H_S} \right| \tag{4}$$

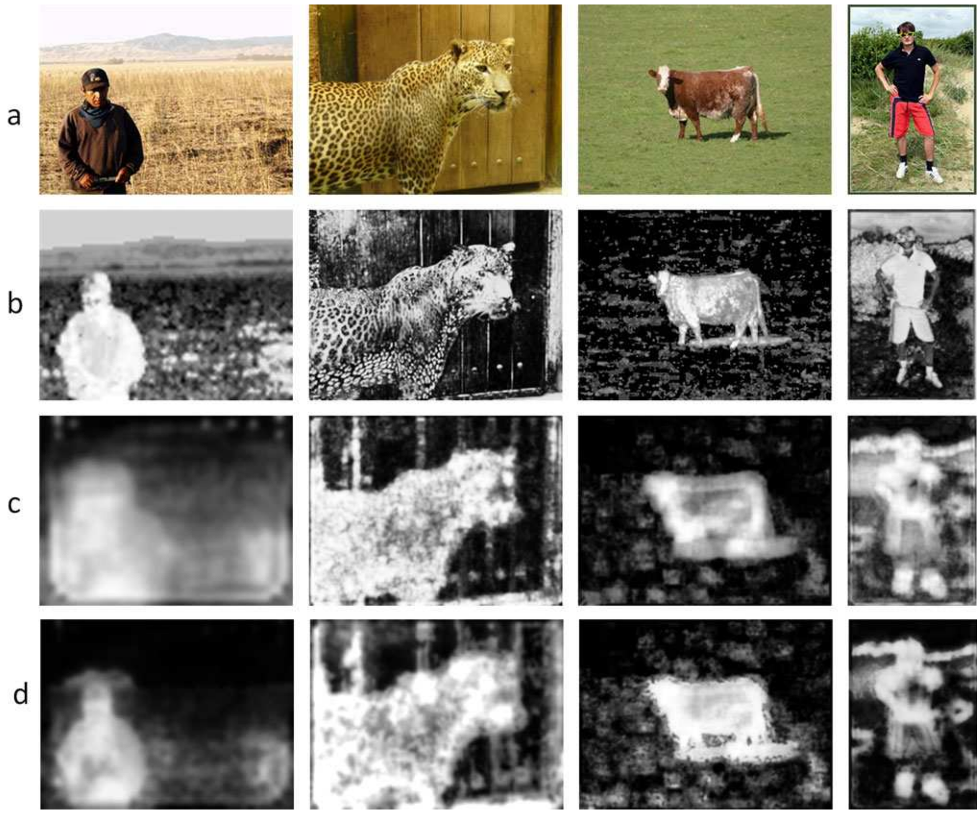

Fig. 3 **a**: Original images, **b**: composite saliency map M, **c**: center-surround saliency D, **d**: final saliency map M_{final}

Calculating the $d(x)$ (4) throughout all the l, ϕ and θ channels, we can compute the resulting center-surround saliency D on a given position (x) as follows in (5). To improve the performance of this feature on images with mixed achromatic and chromatic content, we use a similar approach of hybrid combination of chromaticity and intensity as we used in (3). However, here the color saturation C refers to average saturation over the sliding window P.

$$D(x) = \frac{1}{1-e^{-C}} d_l(x) + \left(1 - \frac{1}{1+e^{-C}}\right) \max\bigl(d_\phi(x), d_\theta(x)\bigr) \qquad (5)$$

By using integral histograms described in [29], all the mentioned histogram operations can be done very efficiently in constant time with respect to parameter p. This parameter permits moreover a top-down control of the attention and of the sensitivity of the feature in scale space. High p value with respect to the image size will make the feature more sensitive to large objects; low values will allow more focus to smaller objects and details. Note however, that all the experiments described further on were carried out with a constant value of p fixed on 20 % of image width (i.e. 72 px for standard 320 × 240 px camera images).

3.4 Final saliency features

As the last step, both the global color saliency $M(x)$ from (3) and the local center-surround feature $D(x)$ from (5) are combined together by application of (6), resulting in final saliency map M_{final}, which is then smoothed by Gaussian filter. The upper part of the condition in (6) describes a particular case, where a part of the image consists of a color, that is not considered salient (i.e. pixels with low $M(x)$ measure), but which is distinct to the surroundings by virtue of its shape.

$$M_{final}(x) = \begin{cases} D(x) & \text{if } M(x) < D(x) \\ \sqrt{M(x)D(x)} & \text{else} \end{cases} \qquad (6)$$

On Fig. 3 some resulting saliency maps of the presented algorithm are shown. Note that for the second image (leopard) the saliency map M (i.e. the global features, row b) does not highlight entirely the leopard's body. This image was selected to illustrate cases, where saliency consists in shape or texture of an object, which is distinct to its surroundings, rather than simply in its color. To capture this aspect of saliency, we compute the second (local) feature over the image: a center-surround difference of histograms (feature inspired by [21]). Regarding the features we use for saliency map calculation, our algorithm belongs to the group of saliency detection approaches, which are not able to cope with psychological patterns like "curve", "intersection", "closure" etc. However, we do not perceive this as a shortcoming as our algorithm is primarily aimed for processing natural images and not to mimic precisely human psychological or vision system.

Having the saliency map of the input image computed, we can proceed to extraction of visually salient objects themselves. This is the purpose on the next section.

4 Salient object extraction

Manual fixed-value thresholding on the final saliency map and automatic thresholding using the Otsu's method have proven themselves as impracticable as well as other statistics based methods that we have applied on the saliency map. The problem is that all these methods work only over the saliency map and do not take into account the original image. Given this observation, we have decided to first apply a segmentation algorithm on the original image to obtain coherent parts of it; then we extract only those segments that are salient enough.

4.1 Main segmentation problems

There are sophisticated techniques for image segmentation like growing-neural-gas approaches applied in real time [4, 14], however we are going to focus in reflectance physics properties of the image for our segmentation process. Let us review some previous definitions about segmentation.

Image segmentation can be defined as a process which divides an image into different regions such that each region has a particular property, but the union of any two adjacent regions is not homogeneous. A formal definition of image segmentation is given in [13]. According to [13]: If $W()$ is a homogeneity predicate defined on groups of connected pixels, then segmentation is a partition of the set F into connected subsets or regions $(S_1, S_2, \dots, S_n)$ such that with $\bigcup_{i=1}^{n} S_i = F$ and $\forall i \neq j,\ S_i \cap S_j = \emptyset$ and $\forall x, y \in S_i; W(x) = W(y)$.

There are four main problems in image segmentation: problems derived of the illumination, noise effects, edge ambiguity and the computational cost. These three first problems are closely related. In segmentation processes the use of a suitable distance measure is very important. Therefore we introduce a hybrid distance which works with intensity and chromaticity. On one hand, this hybrid distance allows parametrization of noise tolerance and on the other hand, we can adapt this distance for optimal edge detection. Furthermore, this distance is grounded in the dichromatic reflection model from [32] by a spherical interpretation of the RGB color space from [27]. So, this approach helps to avoid the first mentioned problem as well. Finally, in this method we will use only the 4-west-nord neighbors; it helps to decrease the computing time. The presented segmentation algorithm has thus the following properties: a good behavior in shadows and shines, avoids the effect of noise and finally it is cheap in terms of computing time.

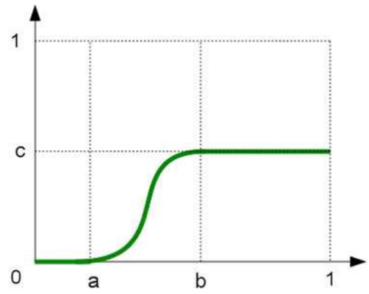

Fig. 4 Chromatic activation function $\alpha(x)$

4.2 Distance

We propose a distance based in the spherical interpretation of the RGB color space. Given an image $\Omega(x) = \{(R, G, B)_x; x \in \mathbb{N}^2\}$ where x refers to the pixel coordinates in the image grid domain, we denote the corresponding spherical representation as $\Omega(x) = \{(\phi, \theta, l)_x; x \in \mathbb{N}^2\}$, which allows us to use $(\phi, \theta)_x$ as the chromaticity representation of the pixel's color.

Empirical experiments tell us that intensity is the most important clue in dark regions, and that on the other hand it is better to use the chromaticity component when the illumination is good. Like in previous works [26] we propose a hybrid distance. Figure 4 shows the chromatic activation function. For values less than a, the chromatic component is inactive, for values that belong to the interval $[a, b]$, we take into account the chromatic component from its minimum energy to its maximum energy c by following a sinusoidal shape. Finally for values bigger than b its energy is always c. The three parameters a, b, c are in the range $[0, 1]$. The region under the green line is the chromatic importance and its complementary, the region over this line is the intensity importance. The function $\alpha(x)$ depends of the image intensity. Its complementary function $\bar{\alpha}(x)$ is the intensity activation function where $\bar{\alpha}(x) = 1 - \alpha(x)$ and hence $\bar{\alpha}(x) + \alpha(x) = 1$. The below equation is the mathematical expression of (x):

$$\alpha(x) = \begin{cases} 0 & x \leq a \\ \frac{c}{2} + \frac{c}{2}\sin(\frac{(x-a)\pi}{b-a} + \pi) & a < x < b \\ c & x \geq b \end{cases} \tag{7}$$

Now we can formulate a hybrid distance between any two pixels p, q as follows:

$$d_h(p, q) = \bar{\alpha}(p, q) \cdot d_l(p, q) + \alpha(p, q) \cdot d_\Psi(p, q) \tag{8}$$

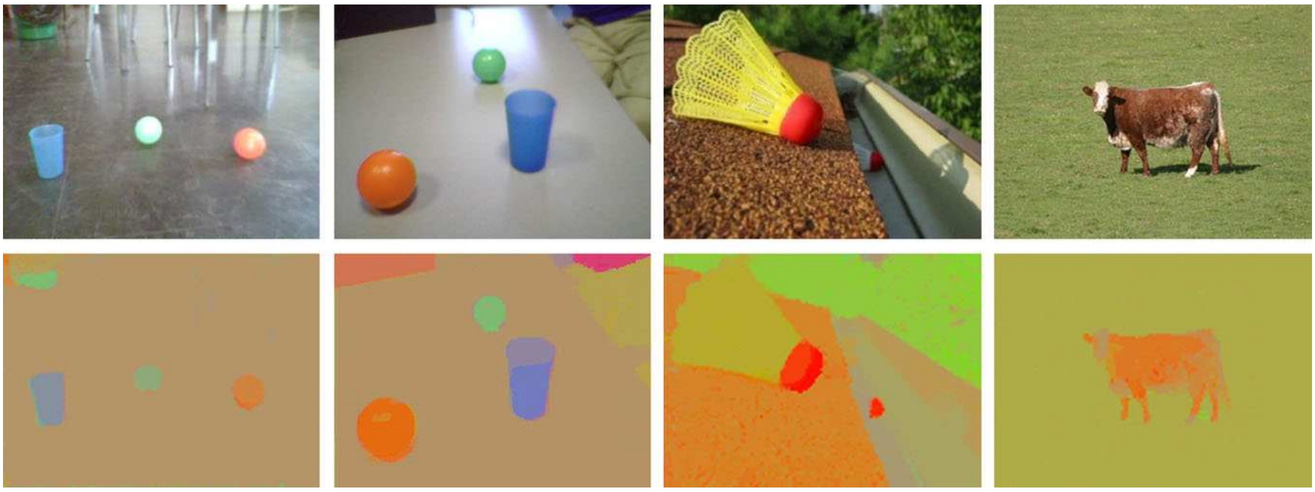

Fig. 5 Sample results of our segmentation algorithm. *Top row*: original images, *bottom row*: resulting segmentation

where the relationship between $\alpha(x)$ and $\alpha(p,q)$ is done by $x = \frac{l_p+l_q}{2}$ where l_p, l_q are the intensities l in spherical coordinates. d_l is an intensity distance as $d_l(p,q) = |l_p - l_q|$ and d_Ψ is a chromatic distance as $d_\Psi(p,q) = \sqrt{(\theta_q - \theta_p)^2 + (\phi_q - \phi_p)^2}$.

4.3 Segmentation algorithm

All of the previously described techniques are joined here covering the four desired goals. On one hand we are going to use the spherical interpretation of the RGB image, and on the other hand we are going to use the aforementioned hybrid distance expressed in Eq. (8). For edge detection a formal gradient is not necessary because it can be calculated "ad-hoc" using our hybrid distance and using a threshold. In fact this method is focused in the detection of homogeneous regions. When the distance between some pixels is less than this threshold we are going to admit that these pixels are homogeneous and then they belong to the same region, otherwise an edge is present.

In order to decrease the computing time, we use a 4-west-nord neighborhood, that is, by columns and rows, computing each pixel only one time. Homogeneous convex regions are easily identified because all of them have the same label. Our method is explained by the algorithm given in appendix. This algorithm returns a bi-dimensional integer matrix of labels. For the computation of this algorithm we also need a structure that relates each label with a chromaticity and the number of pixels labeled with it. That is necessary because each time we assign a new pixel to a label we must actualize the chromaticity of this label, which is the mean chromaticity of all pixels labeled with it. The most important parameter for this algorithm is the threshold δ. The granularity and noise tolerance depend on this. For a very little value we will obtain a lot of small regions, opposed to, with a high value we obtain the large and visually more important regions. On the other hand the parameters a, b, c of Eq. (8) allows to adjust the distance type. If $b = 0$ and $c = 1$ it is a pure chromatic distance. If $a = 1$ it is a pure intensity distance. In other cases it is a hybrid distance. In this algorithm $L(x)$ denotes the label of pixel x, $L_4(x)$ denotes the set of labels of the 4-west-north neighbors of pixel x, that can be expressed as $L_4(x) = \bigcup_{x' \in N_4(x)} L(x')$, where $N_4(x)$ the 4-west-north neighborhood of pixel x. The algorithm may be applied to any color image $\Omega(x)$. It needs the specification of the distance $d_H(x,y)$ that gives a measure of the similarity between pixel colors $\Omega(x)$ and $\Omega(y)$. To label the regions we keep a counter R, and we build a map Ψ_R assigning to each region label a chromatic value. We also have a counter C_R of the number of pixels in the image region of label R.

On Fig. 5, sample results of the described segmentation algorithm are shown. In particular, on first three images, the way how the algorithm reacts to difficult illumination conditions like highlights and shadows is presented. Correct segmentation results are obtained even in presence of strong light and reflections.

4.4 Extraction of salient objects using segmented image

The segmentation algorithm splits an image into a set of chromatically coherent regions. Objects present on the scene are composed of one or multiple such segments. For objects that conform to conditions of "explicitness", the segments forming them should cover areas of saliency map with high overall saliency, while visually unimportant objects and background should have this measure comparatively low.

Input image is thus segmented into connected subsets of pixels or segments $(S_1, S_2, \ldots, S_n)$. For each one of the found segments $S_i \in \{S_1, S_2, \ldots, S_n\}$ its average saliency $\overline{S_i}$

is computed over the saliency map M_{final} as well as the variance of saliency values $Var(S_i)$. All the pixel values $p(x, y) \in S_i$ of the segment are then set following (9), where $t_{\overline{S}}$ and t_{Var} are thresholds for average salience and its variance respectively. The result is a binary map containing a set of connected components $C = \{C_1, C_2, \ldots, C_n\}$ formed by adjacent segments S_i evaluated by (9) as 1. To get rid of noise, a membership condition is imposed that any $C_i \in C$ has its area larger than a given threshold. Finally, we project the binary map on the original image, which gives as a result parts of the original image containing its salient objects. For our experiments, we set $t_{\overline{S}}$ to 50 % of the maximal possible saliency, t_{Var} to 20 and the minimal area to 1 % of total image area.

$$\forall S_i \in \{S_1, S_2, \ldots, S_n\};\ \forall p(x, y) \in S_i;$$
$$p(x, y) = \begin{cases} 1 & \text{if } \overline{S_i} > t_{\overline{S}} \text{ and } Var(S_i) > t_{Var} \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

5 Learning and recognition

The approach described in Sects. 3 and 4 allows us to split an image into a set of fragments, each containing a visually salient object. In this section we explain how we use this to enable a machine vision system to learn an object from unlabeled images. For experiments in real environment described further on we have used a mobile humanoid robot equipped with a color CMOS camera as a source of images. When acquired, images are processed to extract fragments containing salient objects; those fragments are grouped online using approach presented in Sect. 5.1. Only groups with a significant number of members are used as samples database for object recognition methods (see Sect. 5.2), which permits recognition of previously seen objects in different visual context or environment and moreover enables learning multiple objects in the same time.

5.1 Incremental fragment grouping

To preserve as much as possible the on-line and real time nature of learning, we have to group image fragments incrementally as they come from salient object detector with comparatively low calculation efforts. For this task we employ a combination of weak classifiers $\{w_1, w_2, \ldots, w_n\}$, each one classifying a fragment as belonging (result 1) or not belonging (result 0) to a certain class. Each classifier has a high level of false positives but a very low level of false negatives. In our case we employ four weak classifiers ($n = 4$), covering different properties of object on the fragment. A fragment belongs to a class if $\prod_{i=1}^{n} w_i = 1$. A class is allowed to be populated only once by one fragment per image to prevent overpopulation by repeating patterns on the same image. If a fragment is not put into any class by classifiers, a new class is created for it. If a fragment satisfies this equation for multiple classes, it is assigned to the one whose Euclidean distance is smaller in terms of features measured by each classifier (i.e. c_{wn}). Features taken into account by weak classifiers are as follows. In all equations, F denotes the currently processed fragment, whereas G denotes an instance of the group in question. All other symbols are explained further on in the text.

Area: the w_1 in Eq. (10) classifier separates fragments, whose difference of areas is too large. In experiments, we set t_{area} to 10.

$$w_1 = \begin{cases} 1 & \text{if } c_{w1} < t_{area} \\ 0 & \text{otherwise} \end{cases}$$
$$\text{where } c_{w1} = \frac{\max(G_{area}, F_{area})}{\min(G_{area}, F_{area})} \quad (10)$$

Aspect: the w_2 in Eq. (11) classifier separates fragments, whose aspect ratios are too different to belong to the same object. In experiments, we set t_{aspect} to 0.3.

$$w_2 = \begin{cases} 1 & \text{if } c_{w2} < t_{aspect} \\ 0 & \text{otherwise} \end{cases}$$
$$\text{where } c_{w2} = \left| \log\left(\frac{G_{width}}{G_{height}}\right) - \log\left(\frac{F_{width}}{F_{height}}\right) \right| \quad (11)$$

Chromaticity distribution: the w_3 in Eq. (12) classifier separates fragments with clearly different chromaticity. It works over 2D normalized histograms of ϕ and θ component of fragment denoted by $G_{\phi\theta}$ and $F_{\phi\theta}$ respectively with N histogram bins, calculating their intersection. We use N equal to 32 to avoid too sparse histogram and $t_{\phi\theta}$ equal to 0.35.

$$w_3 = \begin{cases} 1 & \text{if } c_{w3} < t_{\phi\theta} \\ 0 & \text{otherwise} \end{cases}$$
$$\text{where } c_{w3} = \frac{\sum_{j=1}^{N-1} \sum_{k=1}^{N-1} \min(G_{\phi\theta}(j,k) - F_{\phi\theta}(j,k))}{L^2} \quad (12)$$

Texture uniformity: the w_4 in Eq. (13) classifier separates fragments, whose texture is too different. We use the measure of texture uniformity calculated over the l channel of fragment. In (13), $p(z_i); i = 0, 1, 2, \ldots, L-1$ is a normalized histogram of l channel of the given fragment and N is the number of histogram bins. In experiments, we use 32 histogram bins to avoid too sparse histogram and value $t_{uniformity}$ of 0.02.

$$w_4 = \begin{cases} 1 & \text{if } c_{w4} < t_{uniformity} \\ 0 & \text{otherwise} \end{cases}$$

$$\text{where } c_{w4} = \left| \sum_{j=0}^{N-1} p_G^2(z_j) - \sum_{k=0}^{N-1} p_F^2(z_k) \right| \tag{13}$$

5.2 Object recognition methods

Although we are able to extract individual objects by means of their visual saliency, this ability alone cannot be used for their further re-detection in different conditions e.g. by a mere comparison of the extracted object with the ones already acquired. It is because there is no guarantee that next time we encounter the object it will be distinct to its surroundings (i.e. salient) and it won't be cluttered or partially obscured by other objects. To cope with this, we use existing object recognition approaches to detect in new conditions the objects we already acquired.

In any time of learning the fragment grouping algorithm provides us a set of groups, each one populated by fragments of images containing the same objects. We can chose any of them and use fragments contained in it as a database of samples for an object recognition algorithm. For detection of objects in context of our system, any suitable real time recognition algorithm can be used. As a demonstration, we have employed two recognition algorithms. Here we will explain the basics of their function and how they make use of data about objects acquired in form of groups of fragments.

The first object recognition technique we used Speed-up Robust Features, or SURF, described in [6] is a well-established technique based on matching interest points on the source image with interest points coming from the template. It provides detection robust to partial occlusions and perspective deformations. In our case we use the fragments acquired as matching templates. To preserve the real-time operation of detection even with high numbers of templates, we pre-extract key points from each template in advance. In the detection stage, we first match several parallel threads templates with the greatest number of key-points (i.e. containing more visual information) and stop this process when another image from the camera arrives. This gives us an opportunity to test up to few tens template matches per frame. Further important speed-up can be achieved using parallel computation power of CUDA-like architectures on modern GPUs.

The second object recognition method, used in our work, is Viola-Jones detection framework published in [34]. Its principle is based on browsing sub-windows over the image and a cascade of classifiers, which determine whether the processed part of image belongs or not to a group of objects on which the classifier was trained. In this case, we use acquired fragments of an object as positive samples to learn the cascade of classifiers (the learning here is carried out offline due to the nature of this method). As this method requires negative samples as well, we use the original images with the learned object replaced by a black rectangle. To be precise enough, the method needs up to several thousands of samples for learning. We achieved this number by applying random contrast changes, perspective deformations and rotation of learning fragments. Although Viola-Jones framework was originally designed to recognize a class of objects (i.e. human faces), rather than single instances, in our case we use it in the way that it recognizes a class of only one object (i.e. the one found on learning fragments). It must be noticed that having the object detector learned, known objects can be detected directly from the input image when seen again, without passing by the salient object detection.

6 Results

As we have written in the introduction of this paper, the goal of this work was to design an intelligent machine vision system able to learn autonomously individual objects present in a real environment. This section is dedicated to present the main obtained results. In first, we begin to present intermediate results about the salient object detection. Although we did not do a comparative study between state of the art saliency methods (e.g. [2] and [21]) and ours, we give some points of comparison. More results and explanations are given in [30]. In Sect. 6.2, we give results obtained on a real robot. Finally, we discuss these results.

6.1 Salient object detection results

On Fig. 6, sample results of our algorithm are compared with ground truth and two others state of the art algorithms. It must be pointed out that our initial goal was not to design a new saliency method but rather to adapt existing approaches in the frame work of robotic applications. These applications imply , especially, robustness and real-time computing. But in order to evaluate the performance of the proposed solution, we have chosen to compare our work with the work presented in [2] and [21] because the first one presents a fast algorithm potentially suitable for real-time application in machine vision, while the latter one shows high performance in terms of precision and correctness. No claims are made by authors of the latter one about its speed, but with respect to the description of the algorithm provided in [21] we assume that it is not suitable for a real-time application.

Figure 6 show results which illustrate the typical performance of presented algorithms. Although [2] is computationally very cheap (saliency map calculation takes about 45 ms on a 320×240 px image), its results vary largely in quality depending on the nature of salient objects on the image. Algorithm of [21] produces results very close to human perception and more precise in terms of resolution (sample results are published online[1]). However, it suffers from

[1] http://research.microsoft.com/en-us/um/people/jiansun/SalientObject/salient_object.htm.

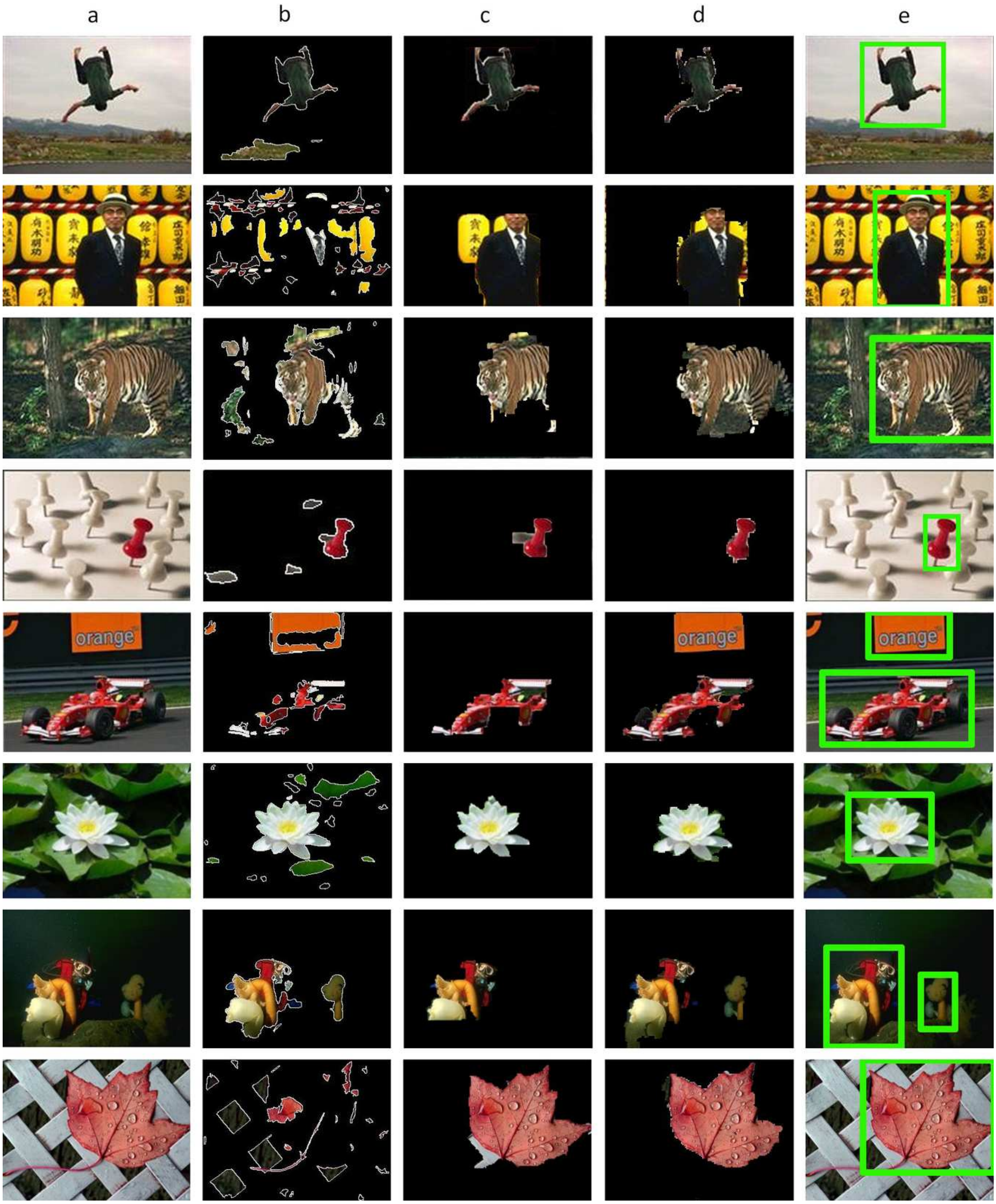

Fig. 6 Comparison of different salient object detection algorithms. **a** *First column*: original image. **b** *Second column*: results of (AC) [2]. **c** *Third column*: results of (LI) [21]. **d** *Fourth column*: results of our approach. **e** *Last column*: ground truth (taking into account multiple objects in the scene).

Table 1 Scores obtained by our salient object detection algorithm on the MRSA dataset

	Precision	Recall	F-measure
Dataset A	0.73	0.75	0.74
Dataset B	0.75	0.76	0.75

two major drawbacks in context of the learning system we present here. It does not claim to be applicable in real time, and more importantly it outputs only one salient objects (i.e. the most salient object) a time (although authors suggest for future work a workaround to this using inhibition-of-return technique). On the other hand our approach outputs natively multiple salient objects if they are present on the image. An illustrative example may be found on Fig. 6, the fifth row, where two visually attractive objects are found on the same image: the F1 racing car and the "orange" logo. As they are both highly salient and clearly distinct in terms of their position on the image, our algorithm marks them both as visually salient. This property appears to be crucial while extracting unknown objects for learning as there is no reason why only the most salient object should be learned, especially in real conditions with highly structured environment and many objects present in the field of view.

We tested our algorithm against the benchmark on MSRA Salient Object Database [21] by using the same protocol. The results are given in Table 1. While these results are close to results obtained by [21] (the F-measure differs from the [21] only by about 0.05), our algorithm brings the benefit of high-speed processing and native output of multiple salient regions, if they are present on the image. In terms of average speed, on 320×240 px the method of AC calculated the saliency map in 45 ms, but takes another 2900 ms per image to extract salient segments using mean-shift segmentation.[2] Our algorithm in its unoptimized version takes in average 100 ms per image (saliency map and image segmentation are calculated in parallel as they are independent processes), which allows us to run it at a speed of about 10 frames per second. All algorithms were run on an Intel i5 CPU at 2.25 Ghz machine.

On Fig. 7 performance of our algorithm in some particular cases is illustrated:

– The case a shows how the algorithm copes with difficult illumination conditions in presence of strong directional light. The ball is extracted correctly and the strong reflection is not marked as a salient object as the shine does not change the chromatic property of the surface.
– In case of b and c, we can observe changes in parameter p of (5). In the first case (high p), the saliency is focused towards larger objects (extracting mainly the human head), whereas in the second case (small p) the emphasis is put on details, which allows to extract eyes, mouth, hair and other small details on the image.
– Finally, cases d and e capture extraction of objects with color and texture close to image background.

6.2 Results of validation a robots' vision

To verify the performance of our system, we have conducted a number of experiments with learning objects present in a common office environment. For the sake of repeatability and convenience in evaluation of results, we have collected ten common house or office objects to be explicitly learned (although the system naturally learns salient objects in its

[2]Based on executable available on http://ivrg.epfl.ch/supplementary_material/RK_CVPR09/index.html.

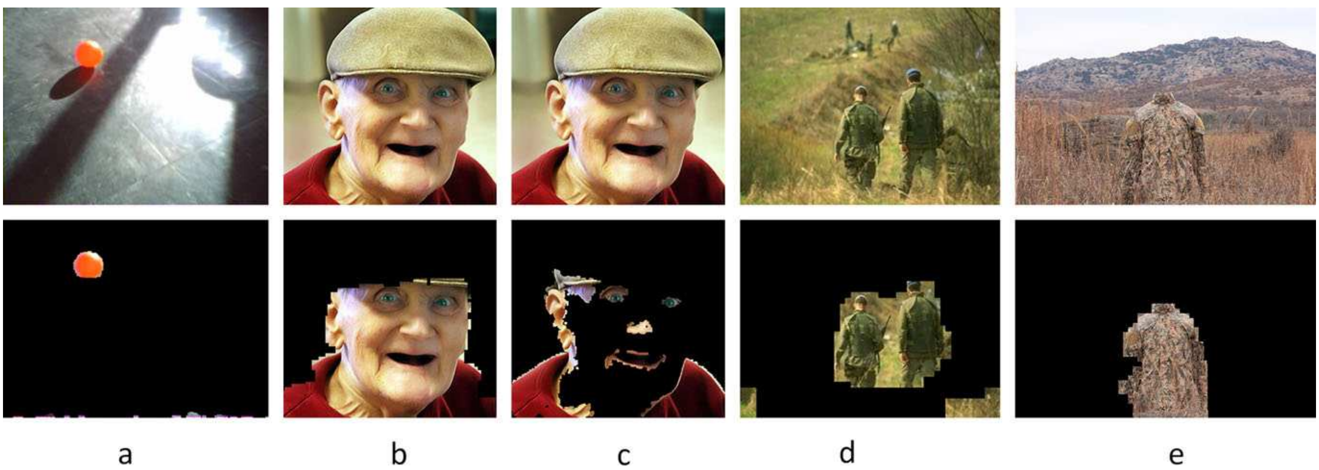

Fig. 7 Particular cases of our algorithm; **a**: conditions of strong illumination with reflections and shadows; **b**: human face with saliency detector focused on large objects; **c**: the same scene with saliency detector focused on small details; **d–e**: objects with camouflage close to the background (soldiers and a military combat uniform)

Fig. 8 Images of objects used throughout described experiments

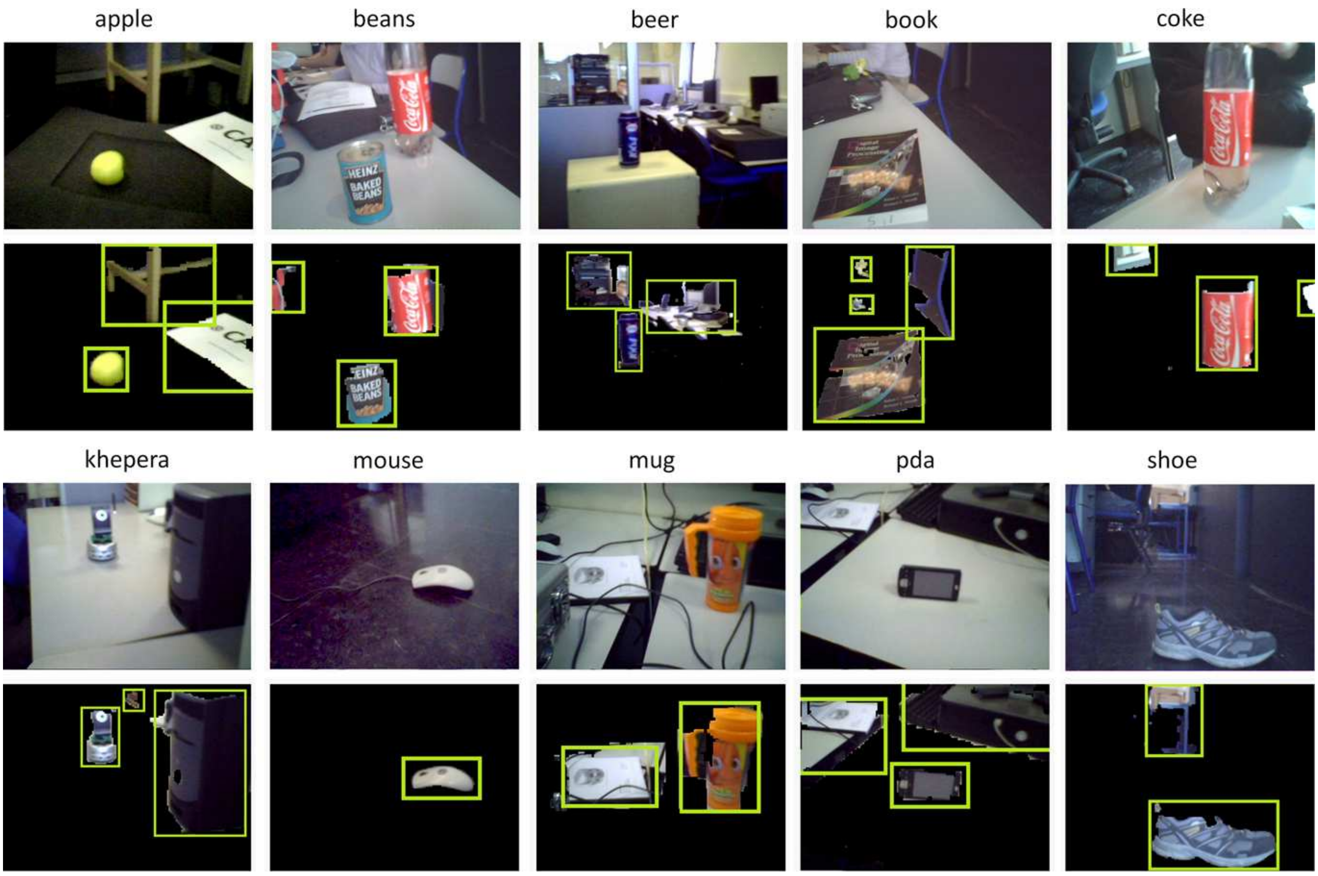

Fig. 9 Sample images from the training sequence for each object. Fragments containing salient objects detected by our algorithm are marked by *rectangles*

surroundings without a specific preference). Illustrative photos of the objects we used in this experiment are shown on Fig. 8 to give the reader a better idea about their nature and a sample of scene images containing those objects is presented of Fig. 9. To approach to the real conditions as much as possible we have chosen objects with different surface properties (chromatic, achromatic, textured, smooth, reflective, . . .) and put them in a wide variety of light conditions and visual contexts. The number of images acquired for scenes containing each object varied between 100 and 600 for learning image sequences and between 50 and 300 for testing sequences, with multiple objects occurring on the same scene. Note that the high number of learning images were taken primarily in order to test our saliency detection and segment grouping algorithm. The learning process itself would generally require significantly less samples ac-

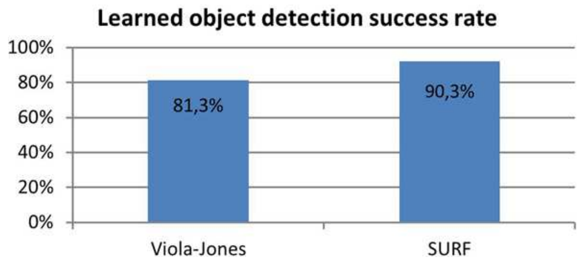

Fig. 10 Percentage of correct detections of learned objects over testing image set using Viola-Jones algorithm and SURF algorithm

quired to perform sufficiently well, depending on the actual object detection algorithm employed. On Fig. 9 random images from the learning sequence are presented for each learned object along with fragments extracted from them. These fragments, containing salient objects found on each image are subsequently processed by the incremental fragment grouping and the selected ones are used for learning of the object detector.

First we present results of salient object extraction and fragment grouping. To investigate the effectiveness of the salient object extraction, we have counted the percentage of learning set images, on which the learned object have been correctly detected and extracted by the salient object detector. Correct extraction means that the object has been extracted entirely and without any other object co-occurring on the fragment. We have achieved successful extraction on 82 % of images in the set. The subsequent grouping of fragments has achieved on the same data-set success rate of 96 %, i.e. only 4 % of fragments (usually bearing visual resemblance to other objects on the scene) were placed into a wrong group, which contained a fragments from a different object. On Fig. 10 detection rates over testing data-set using a trained Viola-Jones detection framework are provided along with performance of SURF algorithm. In average over all the objects in the testing set, the detection rate for Viola-Jones was about 81.3 %. In case of SURF, the average detection rate was higher at about 90.3 %. The numbers reflect only true positive detections. Average rate of false positive detections was insignificant (around 0.5 % in both cases).

To demonstrate real-time abilities of our system, we have successfully run several experiments, where a mobile robot equipped with color camera was required to learn a presented object. When learned, the robot was required to find the object in its environment and to track and follow it. Images from a video[3] acquired during those experiments are shown on Fig. 11. On Fig. 12, sample detection results are shown with a system having learned several objects. Boundary lines determine objects previously encountered by the robot and successfully recognized on the new scene.

[3]This video can be found to the following address http://www.youtube.com/watch?v=xxz3wm3L1pE.

6.3 Discussion

In Sect. 6.1, some qualitative results of our salient object extraction technique were given and compared with existing approaches. We have seen that the quality of our approach is comparable with the existing ones, while bringing advantage of real-time processing, native extraction of multiple salient objects and robustness to certain difficult illumination conditions. This confirms that your salient object extraction technique is performing enough to play its part in the proposed system. On Fig. 9, some qualitative results of our salient object extraction in real environment are given. They show typical views acquired during the learning of the system. Salient objects extracted from them. On all images (except of the "mouse" one, where only one object is present) multiple visually important objects were extracted apart of the one we placed intentionally to the scene, which is a desired behavior as the system is expected to extract (and learn) autonomously the encountered objects without any a-priory preference. On the other hand, as illustrated on the "mouse" and "shoe" images, the algorithm does not extract the "false objects" created by reflections found on the floor. The percentage of successfully extracted samples of a same object usable to learn this object is 82 % of its occurrences throughout a sequence of images. This means that roughly 4 of 5 acquired images of that object contribute in fact to correct learning of this object. As our learning system is incremental, the needed number of sample images for each object can be achieved accurately and fast enough.

We have employed two fundamentally different object recognition algorithms in our system, each yielding a different rate of recognition. The SURF has shown superior performance 90.3 % of average detection rate by contrast to Viola-Jones framework, which performed 9 % worse. This shows that Viola-Jones framework may not be best suited for this kind of task. We presume that it is mainly because of the fact that in order to achieve high recognition rates it typically needs thousands of learning samples, however the number of unique samples acquired for each learned object was in order of hundreds. Also its long learning time makes it impractical in the strict sense of on-line learning. On the other hand results achieved with SURF are encouraging both for the relatively high percentage of correct recognitions and for the fact that it allows recognition of the learned object even with only several samples acquired. Some camera views of

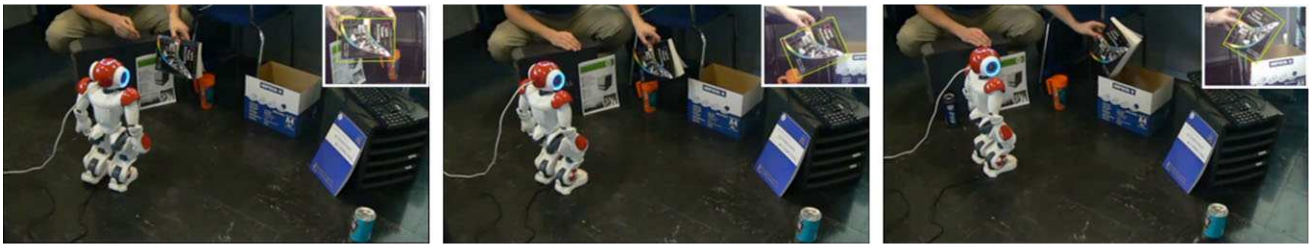

Fig. 11 Images from tracking a previously learned moving object. Robot camera picture is shown in *upper right corner* of *each image*

Fig. 12 Camera pictures from single (*first row*) object detection and multiple (*second row*) previously learned object detection

already learned system are shown on Fig. 12 with recognized objects marked by bounding shapes. On the first row individual objects are correctly detected. On the second row, three views on similar scenes containing multiple objects is shown. Between the scenes the system was progressively learning new objects so that e.g. the orange mug is recognized only on the last scene. The images show flexibility of recognition of the learned objects that are recognized in different orientation and perspective (the book), different illumination conditions (the shoe) or different distance and orientation (the coke bottle).

Regarding experiments with a robot searching for or tracking a previously learned object (Fig. 11), our system was successfully validated. It has enabled the robot to fulfill the required tasks, correctly responding to the input. Because of limited computing capacity of the robot used, we have chosen to run the system on a remote computer. In this experimental context, despite of the specific communication protocol implemented (by the constructor) on the robot, our system itself has been capable of real-time processing performance. However, one may observe a slow-down in robots reactions due to the limited bandwidth. This is the consequence of inadequacy of the aforementioned protocol regarding image transfer.

We have also identified certain shortcomings in learning chain naturally bound to the method of object extraction we are using. In fact, our system shows worsening performance in learning objects that are not visually distinct enough with respect to their background. The same happens in cases where two visually important objects are seen one behind another and thus are wrongly extracted as one by our current system. In effect, in order to respond correctly to this complex situation an additional level of machine intelligence would be necessary. However, it is pertinent to emphasize that in the actual system, once an object is correctly learned, its further detection (thanks to the object detectors employed) is practically independent from its visual context.

7 Conclusion and further work

In this work we have proposed an intelligent machine learning system with capacity of autonomous learning of objects present in real environment. In its conception we were inspired by early processing stages of human visual system. In this context we suggested a novel algorithm for visually salient object detection, taking advantage of using photometric invariants. The algorithm has low complexity and can be run in real-time on contemporary processors. Moreover it exhibits robustness to difficult real-world light conditions. This algorithm is the first key part of the proposed machine vision system. We demonstrate that the detected salient objects can be efficiently used for training the second key part of our system, which is a machine learning-based object detection and recognition unit. Encouraging results were obtained especially when SURF detector was employed as an object detector.

In the future our approach could evolve in several ways. As there does not exist a universal recognition algorithm that suits any existing class of objects, other object detection algorithms, like GLOH in [24] or receptive field co-occurrence histograms in [11], could be adopted along with surface descriptors for each learned object. Objects of different characteristics could be then learned by algorithms that best suit the nature of the object in a "mixture of experts" manner. As to our visual saliency detector, the center-surround feature detector could be supplied by or replaced by an interesting approach of spectral residua detection published in [17]. A top-down feedback based on already acquired and grouped fragments could also greatly improve the saliency detector. The results presented here have been achieved with monocular camera. However, there are reasons to believe that the performance of our system could be enhanced by use of a stereo camera, where the depth-separation of objects would serve side-by-side with the segmentation algorithm to cope with the mentioned cases, where two visually important objects are one behind another.

An open question is, whether the presented technique, instead of learning solely individual objects, could be used as well for place learning and recognition, extracting visually important objects from the entire place like room or office or for visual navigation of a mobile robot. It would also be interesting to investigate, whether the saliency-based method could have an overlap outside the image processing domain, to be applied for learning of other than visual data (e.g. audio).

Appendix: Image segmentation algorithm in siRGB

Input: $\Omega(x)$ //the color image in spherical coordinates
$\delta,\ a,\ b,\ c$ //threshold and three distance parameters values
Output: bi-dimensional matrix L containing pixel labels l and an array of region chromaticity representations $\Psi_l\ \forall\, l$

```
x_0 = Ω(0,0) : L(x_0) = newlabel,  Ψ_{l(x_0)} = Ψ(x_0)
for each x do
    if L_4(x) = {l} then
        //there is only one label in N_4(x)
        evaluate_neighbor (x)
    else
        D ← {d_h(L(y), L(z)) = d_{y,z} | y, z ∈
        N_4(x) & L(y) ≠ L(z)}
        for all d_{y,z} ∈ D s.t. d_{y,z} < δ do
            //region merging
            L(y) = merge(y, z) //merge both regions into
            L(y) Ψ_{L(y)} = avg Ψ(w), ∀w ∈ Ω where
            L(w) = L(y) //update reg. chroma.
        end
        if L_4(x) = {l} then
            //there is only one label in N_4(x)
            evaluate_neighbor (x)
        else
            d ← min{d_h(x, y) | y ∈ N_4(x)}
            if d < δ then
                //assign to region with lower distance
                L(x) = L(y) s.t. d_h(x, y) = d
                Ψ_{L(y)} = avg Ψ(w), ∀w ∈ Ω where
                L(w) = L(y) //update reg. chroma.
            else
                //current pixel cannot be assigned to any
                region
                create_new_label(x)
            end
        end
    end
end
```

```
function: create_new_label(x)
  L(x) = newlabel //create a new region label Ψ_{L(x)} = Ψ(x)
```

```
function: evaluate_neighbor(x)
  d ← min{d_h(x, y) | y ∈ N_4(x)}
if d < δ then
    //neighbor colors are similar
    Ψ_{L(y)} = avg Ψ(w), ∀w ∈ Ω where L(w) = L(y)
    //update reg. chroma.
else
    create_new_label(x)
end
```

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Salient environmental sound detection framework for machine awareness

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ABSTRACT

Auditory perception is an essential part of environment perception, in which the saliency detection is not only the fundamental basis but also an efficient way of achieving this task. For artificial machines, intelligent perception approach of sound is required to provide awareness as the initiatory step of artificial consciousness. In this paper, a novel salient environment sound detection framework for machine awareness is proposed. The framework is based on the heterogeneous saliency features from both image and acoustic channels. To improve the efficiency of proposed framework, (1) a global informative saliency estimation approach is initially proposed based on short-term Shannon entropy; (2) a series of auditory saliency detection methods is presented to obtain the spectral and temporal saliency features from power spectral density and mel-frequency cepstral coefficients, respectively; (3) a computational bio-inspired inhibition of return model is proposed for saliency verification to improve the accuracy of detection; (4) a heterogeneous saliency feature fusion approach is introduced to form the final auditory saliency map by combining the acoustic and image saliency features together. Environmental sounds which collected from real world are applied to verify the superiority of the proposed framework. The results show that, the proposed framework is more effective for the detection of the overlapped salient sounds, and is more robust to the background noise compared with the conventional approach.

1. Introduction

Artificial machines have been widely used in many applications such as advanced industrial manufacture, intelligent robot and unmanned vehicle, thus proved to be powerful tools of modern human society. Though they are far more sophisticated than what human have created before and even appear to be more intelligent, artificial machines still could not behave like self-conscious artifacts as intelligent as human beings. The main reason is that artificial machines are lack of consciousness which distinguish mankind from other species. Therefore, the artificial consciousness is considered as the ultimate goal of artificial intelligence.

Although many consciousness models, such as global workspace model [1], information integration model [2] and attention mechanism model [3], to name a few, have been developed to partly describe the neurobiological and cognitive correlate of human consciousness, they are generally computational models which are implemented to simulate certain aspects of consciousness and are not able to prove that the phenomenal machine consciousness will be possible [4]. Alternatively, a lower level of artificial consciousness called artificial awareness has drawn a lot of attention [5,6]. No matter artificial or natural, the term of awareness in this paper is referred to the state or ability to perceive, to feel, or to be conscious of events or objects which happened or existed in the surrounding environment. The awareness ability of mankind can be seen as the primary stage of consciousness which enables human to accomplish the perception task in an active manner. Therefore, different from the artificial emotion [7], the artificial awareness ability of machine is an alternative way to provide artificial intelligence for machines.

Research from cognitive psychology [8] has demonstrated that bottom-up based selective attention mechanism is an efficient way of perception. When human nervous system is exposed to tremendous amount of environmental stimuli, it is the salient information that guide the allocation of attention as well as the perception resources in human brain. The advantage of this saliency-driven perception process is that only the selectively attended objects, events or locations which stand out of the background will be allowed to progress through cortical hierarchy for high-level processing. At the same time, other research works have also argued that saliency based selective attention mechanism and conscious awareness are closely connected and highly correlated [9]. Consequently, the simulated

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computational model of human saliency mechanism could be a practical path to realize the artificial awareness of machine.

In this paper, we propose a novel biologically inspired salient environment sound detection framework. The framework is based on the heterogeneous saliency features acquired from both visual and acoustic channels. The key contributions of our work are as follows: (1) To provide a global saliency view of sound signal, a wavelet packet decomposition based short-term Shannon entropy (SSE) method is proposed to estimate the background noise. (2) To overcome the overlapping effect of multiple salient sounds, a bio-inspired computational model of inhibition of return (IOR) mechanism is proposed to accurate extract the temporal saliency feature from Mel-frequency cepstral coefficients (MFCC). (3) A power spectral density (PSD) based spectral saliency feature detection method is introduced to detect the salient components in frequency domain. (4) A heterogeneous saliency feature based fusion approach is presented, in which the image saliency feature and the auditory saliency feature are combined to form the final auditory saliency map. The performance of the proposed saliency detection framework is tested experimentally on sound tracks collected from real world environment by which the efficiency and robustness are corroborated.

2. Related works

Currently, research works of saliency-driven auditory perception are mainly based on the auditory saliency map first proposed in the pioneering work of Itti et al. [10]. In Itti's auditory saliency map, the salient sound signal will be represented by the visually specific region with respect to its time-frequency characteristic. Since images and sounds have aesthetic connections in human perception system [11], the auditory saliency can be reformed for perceiving the bottom-up saliency mechanism in the visual domain. Moreover, sound signal could provide omnidirectional information about specific event or object happened or existed in surrounding area, as well as ignoring the influence of obstacles and make the perception more vividly. Saliency-driven auditory perception is also an important research issue regarding the realistic demand in the field of machine awareness. For instance, when a robot is exposed to certain emergency situation like explosion, many salient external stimuli from the same event or object will be received synchronously including the image and sound of either explosion or alarm triggered by the explosion. Since image signal could be blocked by other objects, the sound signal can play a vital role in detection of salient event.

From auditory saliency detection point of view, inspired by the research work of visual saliency map, Kayser et al. [12] initially proposed an auditory saliency map for salient sound detection, in which the auditory saliency model is based on the spectrogram of the input sound signal and the spectrum based auditory saliency maps are obtained by using center-surround difference operator (see [13]) to transform auditory saliency into image saliency for further analyzing. Though experiment results have shown that this model is able to find a salient natural sound among background noise, only the visual saliency features from the image of sound are considered while the information of auditory signal has not been taken into account. The second model is proposed by Kalinli et al. [14] as an improvement of Kayser's work, in which two more features of orientation and pitch are included and a biologically inspired nonlinear local normalization algorithm is used for multi-scale feature integration. Its performance is tested in sound signals of read speech and is proved to be more accurate with 75.9% and 78.1% accuracy on detecting prominent syllables and words. However, in [14] the sound sources are selected from the broadcast read speech database and no environment sound tracks from real world have been used. The third model is proposed by Duangudom et al. [15], in which the spectro-temporal receptive field models and adaptive inhibition are applied to form the saliency map. Supported by the results of the experimental validations consisting of simple examples, good prediction performance can be obtained but the model is still not verified on real environmental sound data which limits its application in industrial manufacture. Recently, Kim et al. [16] considered the Bark-frequency loudness based optimal filtering for auditory salience detection and researched on the collecting annotations of salience in auditory data, in which linear discrimination was used. Though the experiment results shown a 68.0% accuracy, the sound signals for validation are collected from meeting room recordings. This means that only indoor environment is considered. Kaya et al. [17] proposed a temporal saliency map approach for salient sound detection based on five simple features, in which the saliency features only from time domain are considered. Though the test results have shown that this method is superior to Kayser's work, the lack of frequency contrast and other auditory information limit its application. Dennis et al. [18] proposed a salient sound detection approach based on the keypoints of local spectrogram feature for further sound event recognition in which the overlapping effect and noise conditions are considered. Though the experiment results have shown a clear detection output on multiple sound sources, only simple sound examples are used for experimental test and real environment sound signals are not included.

Consequently, the detection of salient environmental sound requires multiple saliency features and the combination of heterogeneous saliency features should be essential to improve the detection accuracy as well.

3. Framework motivation and overview

During the exploration of real world in everyday life of human beings, the perception process is carried out in a very effective and efficient way due to the existence of saliency-driven selective attention mechanism. Despite that the visual perception is dominant in most scenarios, the auditory perception system could provide information of specific events or objects beyond visual range and bypass the obstacles. Hence, sound signal will enable mankind to be aware of and avoid danger beforehand or when human vision is not available in certain environment. However, modern artificial machines like industrial robot still could not perceive its surrounding environment as intelligent as human does, because the perception process is mostly based on the visual sensory information rather than auditory. Another reason is that environmental sound signals are vary in both spatial and frequency properties and require complicated techniques for processing. Therefore, it is essential to provide saliency-driven approach for machine to form the artificial computational awareness ability with respect to the cost of both time and computational resources. Several abovementioned auditory saliency model have shown that it is effective to use spectrogram for auditory saliency detection by transforming auditory saliency into image saliency. However, the deficiencies have also shown that it is a challenge to use only image saliency features for accurate detection. Therefore, the saliency feature of human acoustic characteristic should be considered in order to mimic the human hearing property.

Researches from neurobiology have shown that, in the process of human perception, the detection speed of a detected object will be longer if it has already been attended which means that the attention mechanism prefers to perceive and attend novel stimuli in the environment for efficient purpose, and this orienting phenomenon is referred as the inhibition of return (IOR) mechanism [19]. Though this mechanism is mostly found in visual perception

[20,21], it also reported in human auditory system as well [22]. Due to the IOR mechanism, attention shifting will be determined and reaction will be taken short after the salient sound is perceived by early brain response in a bottom-up pattern [23], along with the fact that environment sound with surprise (i.e., salient) value will more easily influence the spatial orienting attention [24]. Meanwhile, many research works have been conducted to prove that MFCC is a good computational representation of human hearing system and could be extracted as the proper feature for auditory perception for machine perception. Therefore, the MFCC of sound signal is considered as human auditory perception model for acoustic saliency detection by combining it with the computational IOR model to simulate the auditory saliency characteristic of human beings. Furthermore, the saliency features derived from power spectral density (PSD) of sound are applied to detect the salient component in frequency domain in order to improve the detection performance of final auditory saliency map. The overview structure of proposed salient sound detection framework is graphically demonstrated in Fig. 1.

In Fig. 1, module 1 is the background noise estimation process that provides the global saliency information of sound and determines the IOR time for further saliency verification. Module 2 is the image saliency feature extraction process which build on the conventional approaches. Modules 3 and 4 are the temporal and spectral saliency feature extraction procedures, respectively. Furthermore, module 5 is the heterogeneous saliency feature fusion module which outputs the final auditory saliency map.

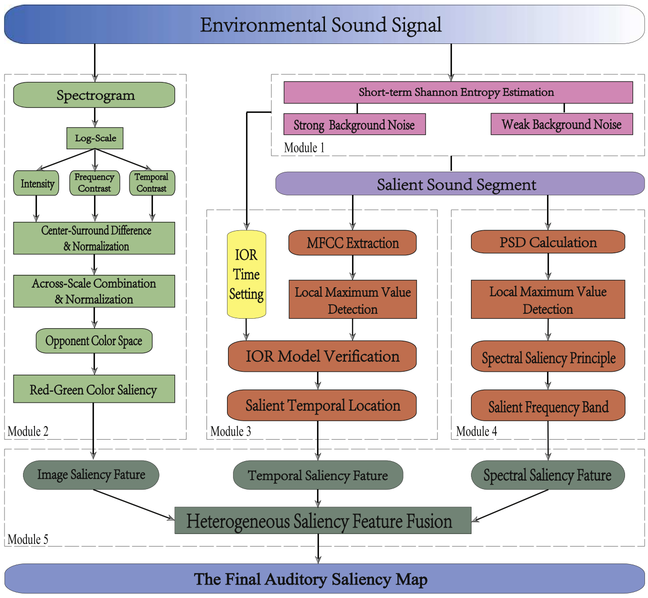

Fig. 1. Overview of proposed saliency detection framework.

4. Heterogeneous saliency feature extraction

The saliency features in the framework are considered to be heterogeneous as they are extracted from both visual and auditory channels and then combined together to form the final auditory saliency map. The whole process of proposed framework can be illustrated in four main stages, which are background noise estimation, local visual saliency feature extraction, local auditory saliency feature extraction and heterogeneous saliency feature fusion, respectively. The detailed procedures are presented as follows.

4.1. Background noise estimation

4.1.1. Shannon entropy

Compare to the visual information perceived by mankind, sound will always exist and real silence is rare because the background noise is almost inevitable even in a tranquil environment. However, human beings are not bothered by this problem because only those sounds which are salient or relevant to one's expectations will be attended. In other words, the uncertain information caused by the salient auditory stimuli will trigger the perception as an instinct of self-protection. In Shannon's information theory [25], the concept of entropy was brought in to measure the uncertainty associated with a random variable. Since the salient sound could be seen as an uncertain signal source compared with its temporal neighborhood within a time period, the Shannon entropy could indicate the quantity of uncertainty information with any distribution contained by the salient sound.

4.1.2. Short-term Shannon entropy

Currently, Shannon entropy is mostly considered to be a feature of signal rather than a saliency estimator in previous research works [26,27], some of which are based on the wavelet packets decomposition. Here we propose a novel short-term wavelet packet Shannon entropy approach to represent and estimate the saliency characteristic of real sound signals. Let S denote the sound signal, and S_i denote the coefficients of S in an orthonormal wavelet packet basis, the Shannon entropy of the ith level of the decomposition is given by

$$El(s_i) = s_i^2 \log(s_i^2), \tag{1}$$

and the Shannon entropy of the entire signal can be given as

$$El(s) = -\sum_i s_i^2 \log(s_i^2). \tag{2}$$

It is obvious that the entropy is an additive cost function such that $E(0) = 0$ and with the convention that $0 \log(0) = 0$. Notably, the Shannon entropy derived from Eq. (2) is a constant value and could not reflect the variation tendency of uncertainty of the signal. Therefore, we divide the sound signal into short-term frames with overlap of 50% and the Shannon entropy of each frame is calculated to represent the average change of the sound signal. Considering the jth frame of N samples of S, the short-term wavelet packet Shannon entropy is defined as

$$E_j(s_j) = -\sum_i s_{i,j}^2 \log(s_{i,j}^2), \tag{3}$$

where $S_{i,j}$ is the coefficients of the jth frame of S in the ith level and the short-term Shannon entropy (SSE) of the entire signal is given as

$$E_f(s) = \sum_{j=1}^{M} E_j(s_j). \tag{4}$$

The value of $E_f(s)$ represents the degree of uncertainty of signal S. Hence, the global estimation of background noise can be given as

$$\mathbf{G}(\mathbf{s_t}) = \begin{cases} \int E_f(s_t \omega(t-\tau)\, d\tau) & \text{if } E_f(s_t) > \sigma; \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

Here, $E_f(s_t)$ is the SSE value of time t, σ is the threshold, and $\omega(t)$ is a window function to smooth the discrete value of SSE for the convenience of saliency detection.

As shown in Eq. (5), the value of $G(s_t)$ will be non-zero and with large value if salient sound occurs or be very small otherwise. Therefore, the background noise could be primary estimated and global saliency information of the sound signal can be provided. To be specific, a sound track has high probabilities to be with strong background noise if $G(s_t)$ is non-zero value dominated, and vice versa. Hence, an empirical discrimination can be defined to estimate the status of background noise as

$$\mathbf{BGN_s} = \begin{cases} 1 & \text{if } 0_n G(s_t)/N < \theta; \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

Here, $0_n G(s_t)$ denotes the number of zero in $G(s_t)$ and N is the length of s_t, θ is the threshold which experimentally set to be 0.4 in this paper. The background noise estimator BGN_s equals 1 when the background noise is strong and indicates a weak background noise level when the value is 0. Note that, the noise status of strong and weak is referred to the global informative characteristic of sound instead of the true loudness. The unequal discriminant in Eq. (6) shows that, when $\theta \times 100\%$ or less of the total number N are zero value points, the sound signal is non-zero value dominated which means that a great part of sound has uncertain information. Since informatic uncertainty represents the potential salient sound segment, the more non-zero values there are, the more potential salient segments exist.

The objective of Eq. (6) is to simply and efficiently estimate the background noise status of sound example for further processing. In general, sound examples recorded in most outdoor environment, especially in urban area, always contain eternal high level background noise, and the BGN_s will equal 1. Therefore, the saliency property of sound is based on the comparison with background noise. Especially, the short-term signal and sound with salient frequency components are the potential candidates for salient sounds. On the contrary, indoor or quiet outdoor environment is expected if the BGN_s equals 0, which means that the specific salient segment including overlapping sounds could be exist.

4.2. Human acoustic saliency model

4.2.1. Acoustic model

Related research works have shown that MFCC is very effective in simulating the acoustic characteristic of human hearing system. It is frequently used as the sound feature in many applications, such as human speech recognition, speaker identification and other audio signal related processing scenarios [28,29]. MFCC is the calculation of cosine transform of short-term energy spectrum's real logarithm into mel-frequency scale, which is defined as follows:

$$mel(s) = 2595 \cdot lg(1 + f/700). \tag{7}$$

The above equation, Eq. (7), shows that the mel-scale frequency $mel(f)$ corresponds to the real frequency in a nonlinear pattern. Therefore, $mel(f)$ is a better computational approximation of human hearing system in cochlea than linearly spaced frequency bands because it simulates the nonlinear hearing sensitivity of human acoustic property to different sounds in different frequencies. Meanwhile, $mel(f)$ can also be seen as a subjective representation of the frequency feature of sound to the human awareness ability. In this paper, $mel(f)$ is implemented by a series of triangular band pass filters with scales of 12, and the MFCC is the result after converting the log mel spectrum into time domain.

4.2.2. Temporal acoustic saliency detection

Human beings always intend to be attracted by the sounds with higher frequency components. Thus sounds with lower frequency components could be considered as pseudo background noise. Regarding the environmental sounds with low frequency components, the sound with salient loudness level among its neighborhood in temporal domain could also be perceived as salient sound. This saliency-driven selective attention mechanism can also be explained by the previous mentioned IOR phenomena which elucidates that new sound with a surprise value will be perceived more quickly than those sounds vary within a certain interval in spectral domain. This is the reason why we are sensitive to the spike-form short-term sound signal even a current salient sound has been attended.

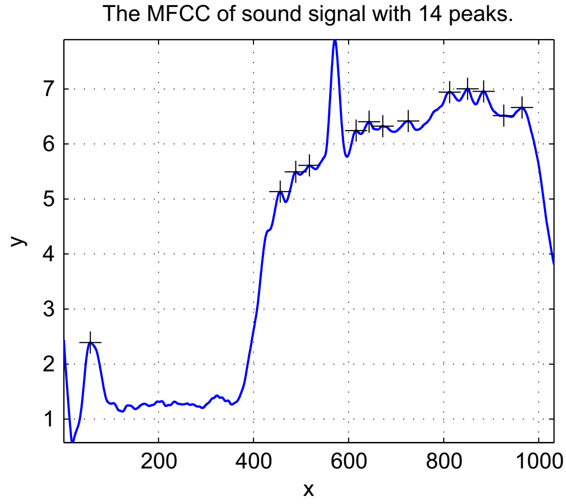

Fig. 2. The detection result of local maximum value. The maximum point with amplitude over 7 is the expected salient sound while others are mis-detected results.

To mimicking the acoustic saliency detection of human beings, the MFCC of sound is considered to be the main representation of human hearing system and the salient sound is indicated by the local maximum value of MFCC. However, there do exist the possibility that pseudo peaks in MFCC curve are irrelevant to the salient sound detection. An example is given in Fig. 2 to illustrate this drawback of purely mathematical approach.

Therefore, we propose a computational IOR model based saliency detection approach to locate the most salient sound in temporal domain. Assuming there are p local maximum points of MFCC have been detected, the real salient points are the ones with a minimum time interval between their two neighbor points.

Psychology and neurobiology researches [23,21] have shown that, stimuli with the stimulus onset asynchronies (SOA) within 200 ms are considered anticipatory response and facilitation effect occurred, while valid cues delay reaction times (RTs) relative to the invalid cues at longer SOAs (over 400 ms). This phenomena also supported by other research works [30–32] which experimentally demonstrated that, facilitation can be found with SOAs of 450 ms in infants or schizophrenics and between 360 and 570 ms in younger children. To simplified the calculation, the inhibitory effect of temporal saliency can be determined by using a minimum time interval t_{IOR} defined as

$$\mathbf{t_{IOR}} = \begin{cases} 200\text{ ms} & \text{if } \mathrm{BGN_s} = 1; \\ 450\text{ ms} & \text{if } \mathrm{BGN_s} = 0. \end{cases} \tag{8}$$

In Eq. (8), our general assumption is that two local salient points within t_{IOR} will be considered as non-salient points. This can be explained by the IOR mechanism that, if the time interval between two temporal adjoining local salient points is less than t_{IOR}, facilitation will occurred and inhibitory effect is not obvious, so the latter salient point will be treated as non-surprise point by auditory perception system. Hence, the local salient points will be processed as current background noise. However, it is also possible that the local salient points represent a real salient sound globally, which means that they could be the reflection of local change in frequency patterns. Therefore, by combining other saliency features, the local salient points can be considered as pseudo background noise and a more salient sound is expected.

Since background noise is a crucial factor to salient sound detection, it is necessary to model IOR mechanism according to the differential in background noise level. Biologically speaking, when we exposed to multiple sounds as well as background noise, both sounds and noises will be perceived as input stimuli at the same time. If the background noise level is strong, the caused facilitation effect will be in a higher level, and sounds within t_{IOR} will be masked by the noise. Conversely, if the background noise level is weak, the auditory perception system will be more sensitive to non-noise sounds. Meanwhile, due to a lower level of facilitation effect, the auditory perception will be influenced by overlapped salient sounds, in which facilitation will caused by the less salient sounds. Thus, the quasi-salient sounds could be treated as pseudo background noise and the more salient sounds are expected.

Moreover, as strong background noise can be seen as multiple temporal stimuli that closed to each other, here we choose the general accepted minimum time length of SOAs of 200 ms to represent the facilitation process. Consequently, those separate stimuli in sound longer than 200 ms are the candidates of real salient sounds. Regarding the sounds under weak background noise, since facilitation caused by noise will be in a lower level, we could be more affected by the facilitation generated by the quasi-salient sounds. In other words, our auditory perception system is intend to perceive new sounds even a current salient sound has been attended. From a biology point of view, the most salient sound in overlapped period to human auditory perception is mostly the short term separate sound signal, which means that the long term salient sounds would be frequently considered as the pseudo background noise. According to the neurobiology researches in IOR phenomena, we experimentally set the t_{IOR} to be 450 ms in weak background noise environment.

In addition to abovementioned temporal requirement of IOR model, we assume that the detected point should also have a salient value of MFCC even if it has satisfied Eq. (8) already. The mechanism of IOR shows that, under the circumstance that overlapped salient sounds exist, if one salient sound occurred and attended, the auditory perception system is expecting or more sensitive to a more salient sound. On the other hand, the decrease of salient MFCC value also indicates the saliency properties of sounds. To be specific, for two adjoining salient points which has meet the requirement of Eq. (8) if the first salient point has been assigned as candidate of the most salient sound, there should be a significant decrease between the MFCC value of these two points. Otherwise, the candidate does not represent the real salient sound and probably is the local saliency representation of pseudo background noise. Therefore, the expectation value of MFCC for p point can be calculated as

$$M_{IOR_+,p+1} = M_p(e^{t/t_{IOR}} \cdot \alpha)^{-1}, \tag{9}$$

$$M_{IOR_-,p+1} = M_p(e^{t/t_{IOR}} \cdot \beta), \tag{10}$$

where M_p is the MFCC value of p point, t is the time length between p salient point and $p+1$ salient point, α and β are the adjustment coefficients. It is obviously that $M_{IOR_+,p+1} > M_{IOR_-,p+1}$. $M_{IOR_+,p+1}$ and $M_{IOR_-,p+1}$ are the two threshold values, which respectively represent the upper limit and the lower limit of the expectation value for the detected $p+1$ salient point. Eqs. (9) and (10) simulate the saliency detection principle that influenced by the IOR mechanism, in which the initiate value of M_{IOR_+} and M_{IOR_-} is high and will decrease as time lapses. Furthermore, considering the existence of overlapping, the most salient sound of p point can be detected by the inequable discriminator if

$$M_p \geq M_{IOR_+,p-1} \bigcap M_{p+1} \leq M_{IOR_-,p}. \tag{11}$$

Consequently, the most salient sound can be detected among background noise or other relatively salient sounds.

4.2.3. Spectral acoustic saliency detection

Several auditory saliency models have been proposed to reveal the saliency characteristic of sound and proved to be effective as mentioned in previous section. However, most saliency features are derived from local contrast while global saliency information is rarely taken into account. Therefore, we propose to take global saliency feature from the power spectral density (PSD) estimation of a given sound signal to obtain the salient frequency component distribution as a complementary part of the traditional auditory saliency model.

The PSD calculation process of a given sound signal is that, divide the sound signal into several overlapping segments by applying a window function to each segment and then averaging the periodogram of each segment thereafter. As the estimation result indicates the power distribution of signal at different frequencies, the local maximum point in the spectrum curve can be used to locate the salient components of sound signal in spectral domain.

Assuming that the local maximum value points have been detected in the curve of PSD which indicate the potential salient frequency components, we compare each point with P_{mean} which is the mean value of PSD and ignore the pseudo salient point that less than P_{mean}. Meanwhile, the frequency range of human hearing system is conventionally on average from 20 Hz to 20 kHz, but the lower and upper limits of this range can only be heard to very few people. To most of the adult individuals, the audible sounds in real world are with frequencies from 40 Hz to 16 kHz in an unequal sensitivity pattern and great sensitivity can be achieved normally in the frequency range 2 kHz–5 kHz. Furthermore, two sounds with different loudness can be distinguished if the physical level increases by 10 dB [33]. Therefore, the salient frequency components that above 15 kHz will be reassigned as nonsalient, and for the rest q salient points, the frequency axis of PSD will be divided into $q+1$ bands as

$$(0,f_1),(f_1,f_2),\ldots,(f_{q-1},f_q),(f_q,f_{P_{mean}}),$$

where f_q and $f_{P_{mean}}$ denote the location in frequency axis of q salient point and P_{mean} point. Then we find local minimum value $P_{localmin,j}$ in the jth band and check the saliency by

$$\mathbf{S}_{PSD,q} = \begin{cases} 1 & \text{if } \mathbf{P}_q - \forall(P_{localmin,j}, P_{localmin,j+1}) > \zeta; \\ 0 & \text{otherwise}. \end{cases} \tag{12}$$

Here, ζ is the saliency distance that equals 10 dB, $S_{PSD,q}$ indicates the true saliency property of q point. Therefore, those salient points in PSD with $S_{PSD,q}=1$ are the real salient frequency components with more power spectral density energy. They will be processed in the conventional auditory saliency map within a spectral period of $(f_q \pm 500\ \text{Hz})$ to decrease the computational cost. Nevertheless, if $S_{PSD,q}=0$ for all the q points, it means that no salient frequency component exists. Thus, there is a great possibility that the background noise is too strong or the sound signal has widely distributed frequency component, then the temporal saliency features play a vital role in the saliency detection process.

4.3. Heterogeneous saliency feature fusion for auditory saliency detection

Generally, saliency maps generated from conventional auditory saliency models are based on the time-frequency representation of sound signal. However, only local image saliency features from spectrogram are applied. Though it has been proved that these models are effective, the efficiency in dealing with background noise and especially the real environmental sound signals is yet in a preliminary level. Therefore, the heterogeneous saliency features should be combined together to output a final auditory saliency map. To be specific, the global and local saliency features from both image and auditory channels should be fused for accurate detection and overlapping salient sounds separation.

Firstly, to depress the affect of background noise and emphasize the salient sound signal components, the original spectrogram is transformed into log scale. Assuming that the original spectrogram is I_s, the log scale spectrogram I_g is calculated as

$$I_g = 20\log_{10}(|I_s|^2/60). \tag{13}$$

In I_g based time-frequency representation of sound, signal components with higher power energy will be represented by the red region in RGB color space while lower power components are commonly in green. However, the human perception of color is not best represented in RGB color space according to the opponent-process theory [34], a better model of opponent color space is proposed in which the red and green colors are postulated as opponent colors. Hence, as the salient time-frequency components of sound signals with red color are more salient to human vision among background or spatiotemporal neighborhood with green color, the image saliency can be derived from the red–green channel [35] of opponent color space which defined as

$$I_{red-green} = (I_g(RGB_r) - I_g(RGB_g)), \tag{14}$$

where the RGB_r and RGB_g are the red and green channel of original RGB color space, respectively. As a result, a spatiotemporal saliency map based on spectrogram is obtained by combining the auditory saliency feature of salient M_t from temporal domain and saliency feature from spectral domain of $S_{PSD,q}$ together. Thereafter, the final auditory saliency map is generated by fusing the image saliency feature from I_g. The general fusion process can be shown as

$$S_{image} = I_{red-green} \cap \{S_{SSE}\}. \tag{15}$$

$$\mathbf{S}_{acoustic} = \begin{cases} \{S_{M_p}\} \cup \{S_{PSD,q}\} & \text{if } \mathbf{S}_{PSD,q} \neq \varnothing; \\ \{S_{M_p}\} \cap \{S_{P>P_{mean}}\} & \text{if } \mathbf{S}_{PSD,q} = \varnothing. \end{cases} \tag{16}$$

$$\mathbf{S} = \begin{cases} S_{image} \oplus S_{acoustic} & \text{if } \mathbf{BGN}_s = 1; \\ S_{image} \oplus (S_{image} \| S_{acoustic}) & \text{if } \mathbf{BGN}_s = 0. \end{cases} \tag{17}$$

Here, S_{SSE} is the set that represents the salient parts of sound signal with $G_{st} \neq 0$, $\{S_{M_p}\}$ is the set that contains the temporal locations of salient signals indicated by the salient MFCC value after IOR test, the set of $\{S_{P>P_{mean}}\}$ represents the salient parts of which the PSD values are greater than P_{mean}. Eq. (16) shows that, when the constraint of spectral saliency $\{S_{PSD,q}\}$ is strong (i.e., non-empty set), the fusion is conducted by using a union operation, while the constraint of spectral saliency $\{S_{PSD,q}\}$ is weak (i.e., null set), the fusion is carried out by using an intersection operation in which $\{S_{P>P_{mean}}\}$ set is applied. Eq. (17) shows that, the final saliency map is derived from the fusion of image and auditory saliency features when the background noise is strong; while in the weak background noise, the final auditory saliency map is obtained by fusing the image saliency feature and correlated auditory saliency dominant image saliency feature together.

5. Experiments

5.1. Experiment setup

In order to verify the performance of proposed auditory saliency detection framework in dealing with sound signal occurred in real environment, two sound examples recorded in real outdoor environment are used. Each example contains at least one kind of sound occurred in everyday life which are salient to human awareness. Meanwhile, the properties of salient sounds contained in the sound examples are vary in both spectral and temporal domain.

To be specific, example A recorded the sound event of police car deploying in which the salient sounds contain a siren of police car with two different frequency patterns and a sudden beep. Example B is a record of festival march in which the salient sounds to human hearing awareness are the multiple sounds of the horse's hoof hitting the ground. The background noises are included in both of the sound examples but vary in the loudness level. Respectively, the background noise exists in example A is rarely salient to the police siren, while the difficulty of auditory saliency is to distinguish the sudden beep of truck from the salient sound of police siren as background noise. The background noise exists in example B is at a very high level and almost as strong as the sounds of horse's hoof hitting the ground which are salient to human awareness.

The most salient sound of truck beep from example A and the salient sound from example B are typical short-term sound signals which could be masked by the background noise or any less salient sounds. The frame length of SSE is 1024 points with an overlap of 512 points and the scales of mel-scale filter bank are 20. The coefficients α and β in Eqs. (9) and (10) are empirically set to 0.133 and 0.114, respectively.

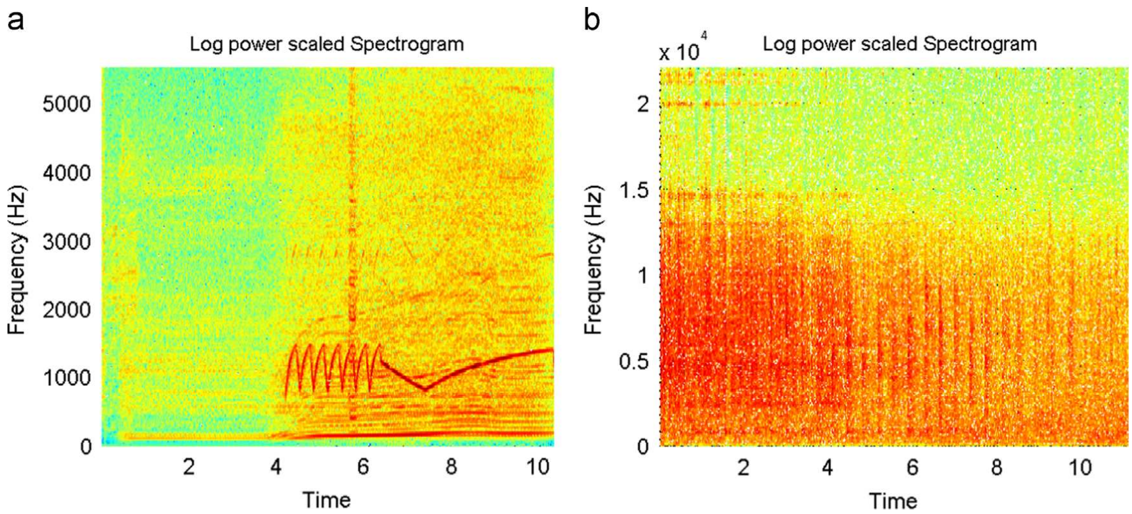

Fig. 3. The original spectrogram of experiment sound example A in (a) and example B in (b). (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

5.2. Experiment results and analysis

The proposed saliency detection framework is applied to the two sound examples A and B, and the multiple results of detection processes are graphically demonstrated in Figs. 3–10. To verify the performance of proposed framework, results derived from conventional approach of Kayser's work [12] is presented in Fig. 11.

The experimental results of saliency detection process as well as the final auditory saliency map are demonstrated in Figs. 3–11. The original spectrograms in log scale of the two sound examples are presented in Fig. 3, in which the salient sound signals are represented by the red color regions. In Fig. 3(a), three salient sounds to human auditory awareness are distinguishable for human visual awareness in the log-scale spectrogram, in which the polygonal lines with salient red color in the low frequency region of spectrogram indicate the two salient sounds with different spectral patterns and a salient vertical line with red color which is salient to its neighborhood indicates the sudden beep of the truck in sound example A. In Fig. 3(b), almost the entire spectrogram less than 15 kHz is in red color through which the salient sounds of horse's hoof hitting the ground are extremely difficult to be detected for human visual awareness due to the strong background noise, while the salient sounds could be distinguished by human beings with auditory awareness.

The SSE and normalized SSE calculation results of sound example A and B are demonstrated in Figs. 4 and 5, respectively. Figs. 4(a) and 5(a) show that there is a long period in which the values of SSE and normalized SSE are close to zero, which indicate that the global background noise in example A is not strong. Therefore, only the salient period with values over the threshold θ of SSE and normalized SSE which represent the global temporal location of salient sound signals will be allowed for further processing. Thus the computational cost could be decreased. Meanwhile, the SSE and normalized SSE of example B in Figs. 4(b) and 5(b) show that almost the entire sound example has the saliency property because of the strong background noise and the further saliency detection is required.

Results from Fig. 6 illustrate the primary saliency detection results in MFCC of the two experiment sound examples, in which the plus sign indicates the location of local maximum value point. It is obvious from both Fig. 6(a) and (b) that multiple local maximum value points have been detected. However, to human hearing awareness, only one plus sign (the fifth from left) in Fig. 6(a) represents the temporal location of most salient sound while others are mismatched points. From Fig. 6(b), it can be seen that most of the salient sound signals have been located in MFCC. However, the last three salient points are yet mismatched according to human auditory saliency property. This is because that all the salient points are locally maximum and could not provide a global saliency information of sound. Furthermore, Fig. 7 shows that most of the local maximum value points detected in PSD are mismatched as well. Specifically, the real salient spectral component in Fig. 7(a) is represented by only one salient point (the third from left), and no salient component exists in Fig. 7(b) because the values of PSD which are more than P_{mean} have no global maximum point. Thus, the saliency detection result in Fig. 7(b) has no corresponding relationship with the spectral saliency feature of salient sound, which bring in the requirement of further saliency verification process if the salient sounds have no specific salient frequency band.

In Fig. 8, the two images show the temporal saliency feature from MFCC of both example A and B after using the computational IOR model for verification. Fig. 8(a) clearly demonstrates that the most salient sound has been accurately detected after the IOR test while other mismatched points are ignored. Relatively, the temporal saliency feature detection result of example B is presented in the right image, in which the mismatched salient points at the end of the sound example have been removed. The spectral saliency feature detection results are demonstrated in Fig. 9, in which Fig. 9(a) shows that the salient frequency component has been correctly detected and located. The local maximum value point which correlates to the background noise at lower frequency band is ignored. Fig. 9(b) shows that, though there are several individually salient points detected in the PSD curve of example B, no authentic salient points exist after using the spectral saliency verification Eq. (12). Hence, it indicates that frequency components with PSD value that over P_{mean} should be entirely considered as the spectral saliency feature for detection.

The final auditory saliency detection results of proposed framework are given in Fig. 10 in the form of auditory saliency map. The detection results derived from Kayser's work are presented in Fig. 11 for comparison. It is shown that, the salient sounds in both the two examples have been successfully detected by the proposed framework and clearly represented by the auditory saliency maps. To be specific, as shown in Fig. 10(a), the overlapped salient sound of the sudden beep of truck in example A has been accurately detected among the salient background which consists of two patterns of police car siren.

However, Fig. 11(a) shows that this salient sound of beep has not been correctly detected in Kayser's auditory saliency map, since its visual representation can hardly be distinguished from the background noise due to the reason of sharing a similar color. Similarly, Fig. 11(b) shows that the multiple salient sounds of horse's hoof

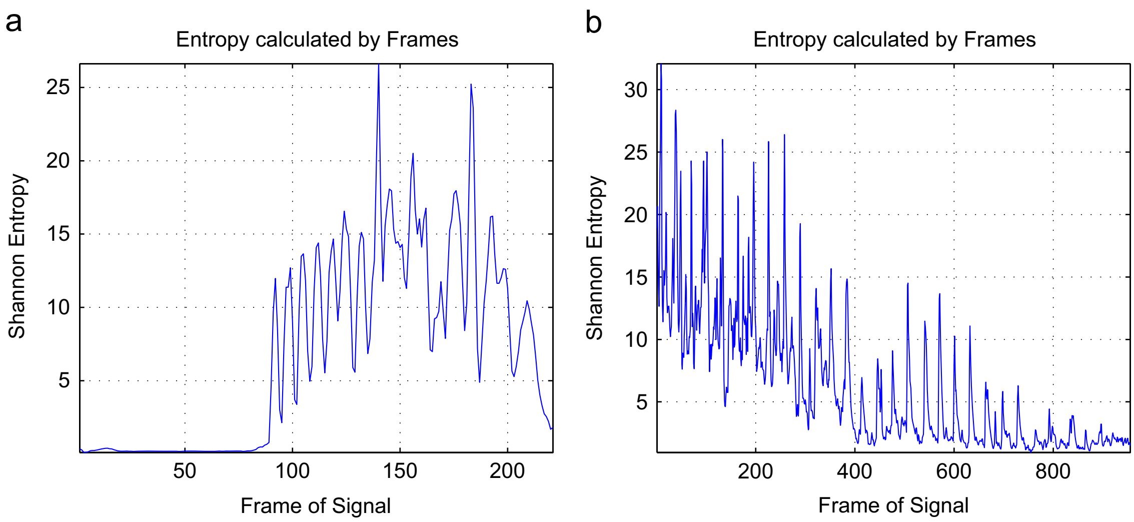

Fig. 4. The short-term Shannon entropy of experiment sound example A in (a) and example B in (b).

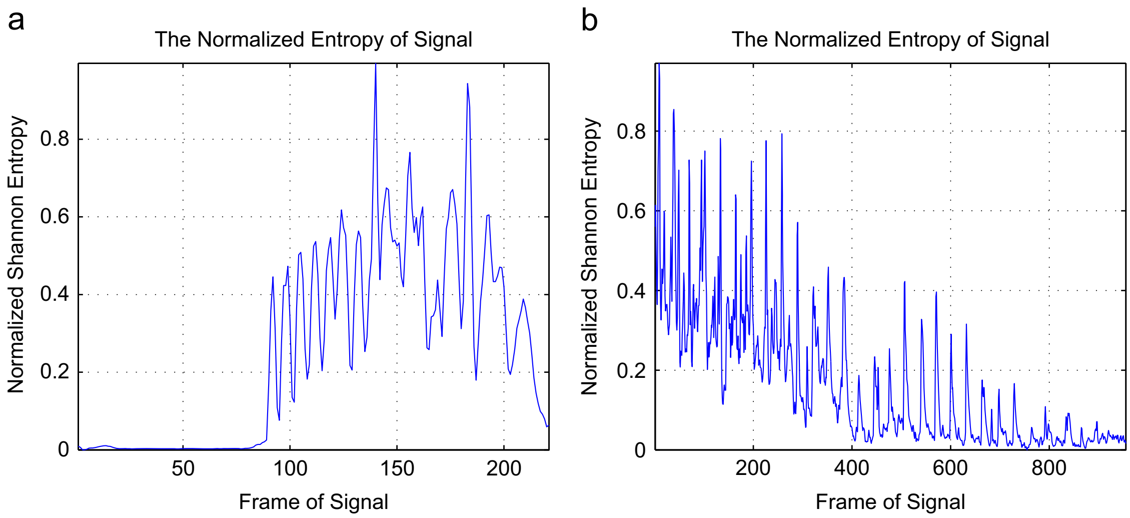

Fig. 5. The normalized short-term Shannon entropy of experiment sound example A in (a) and example B in (b).

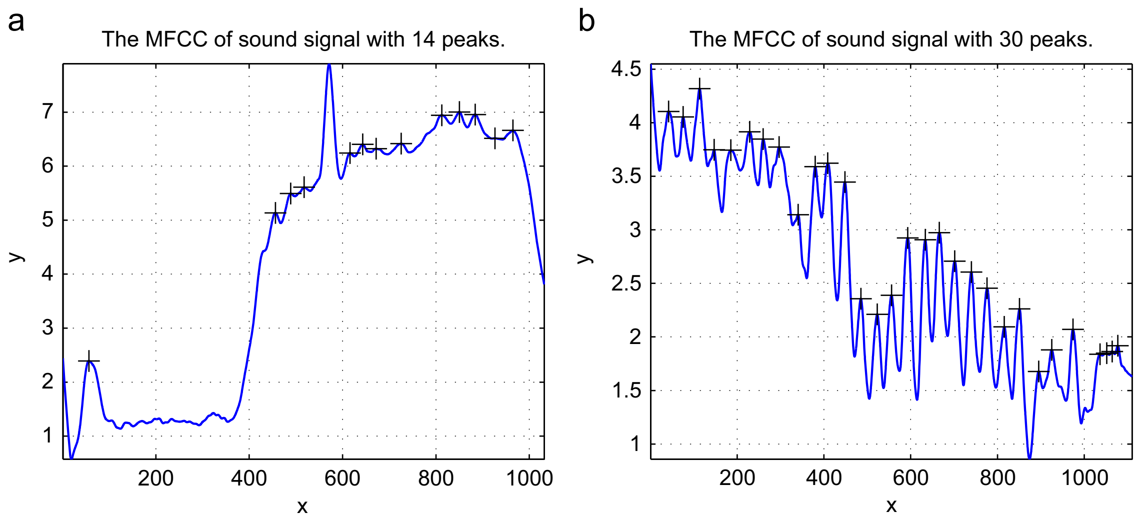

Fig. 6. The saliency detection results from MFCC of experiment sound example A in (a) and example B in (b).

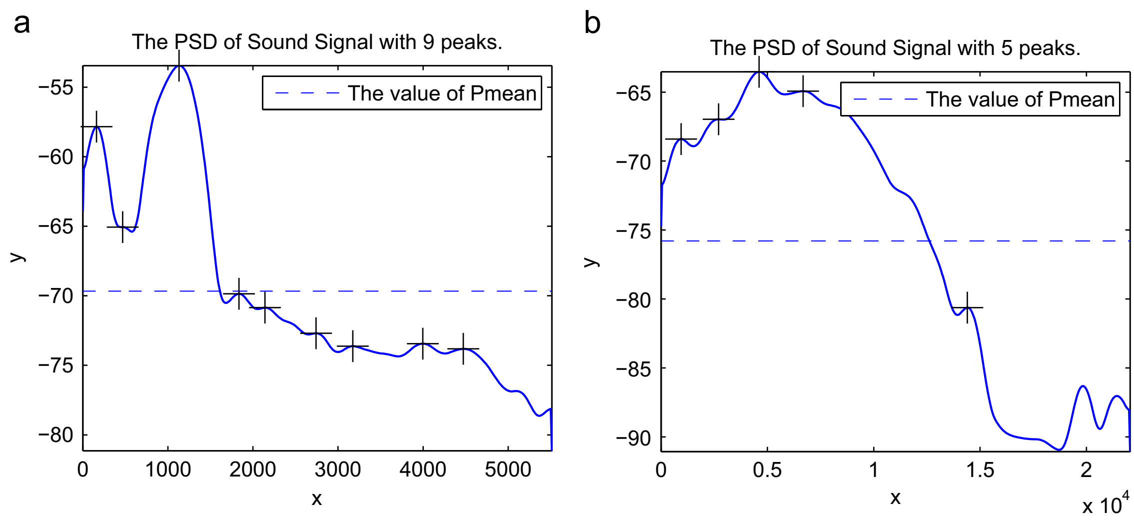

Fig. 7. The saliency detection results from PSD of experiment sound example A in (a) and example B in (b).

hitting to the ground have not been detected by the Kayser's approach, because the visual representations of these salient sounds are not clear and distinguishable. They are visually similar to the visual representation of background noise, and the saliency features derived from the auditory saliency map have little corresponding relationship to the original salient sounds. Correspondingly, as

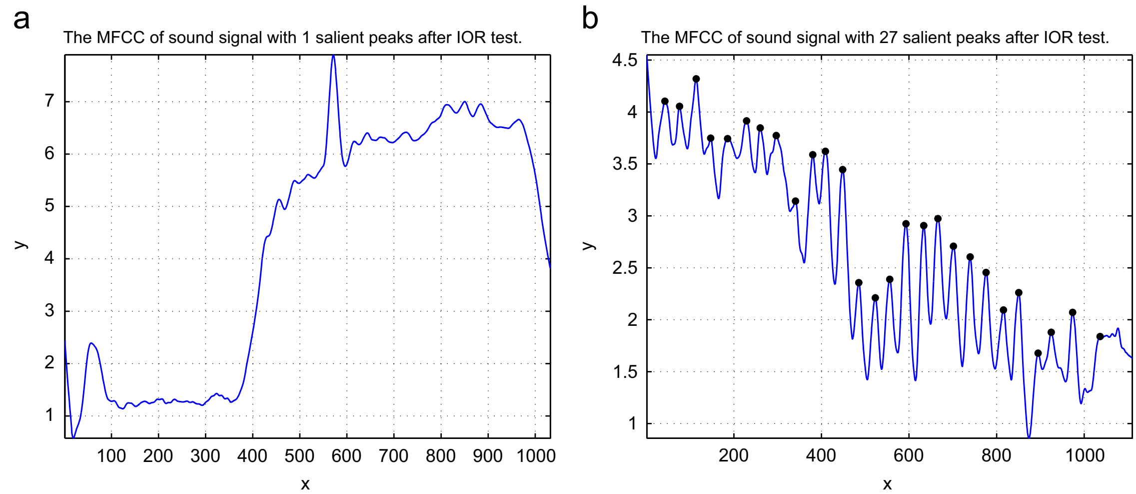

Fig. 8. The saliency feature obtained from MFCC after IOR test of experiment sound example A in (a) and example B in (b).

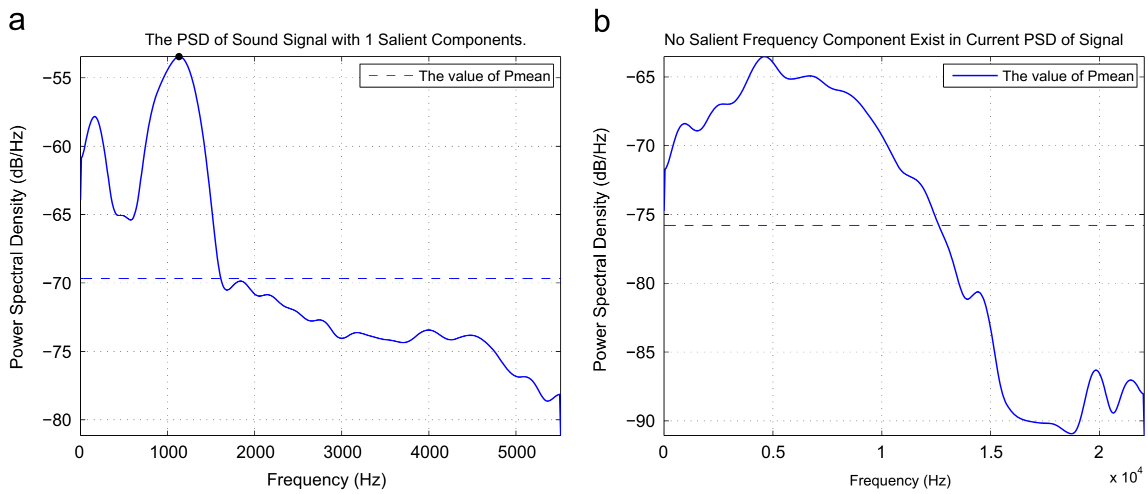

Fig. 9. The saliency feature obtained from PSD of experiment sound example A in (a) and example B in (b).

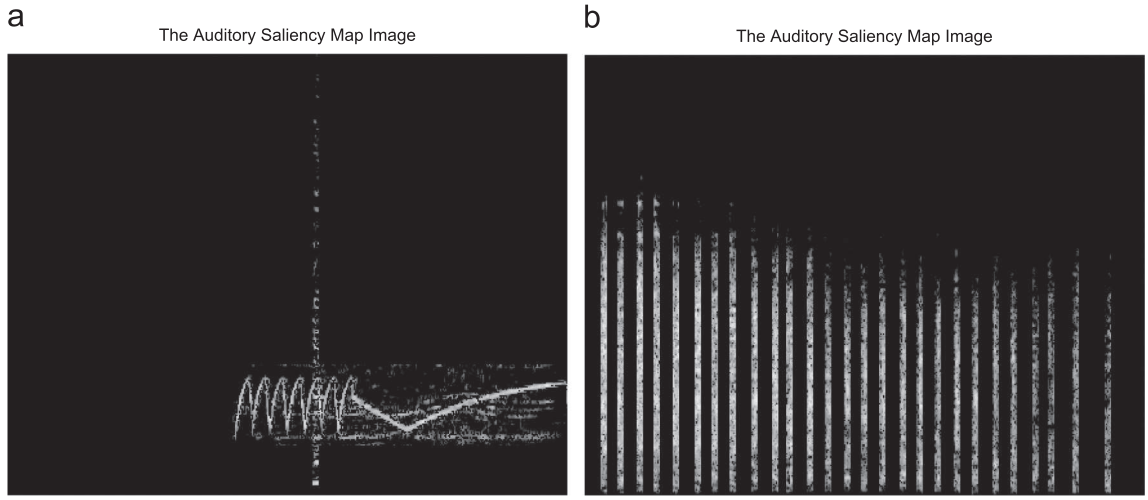

Fig. 10. The final auditory saliency map of experiment sound example A in (a) and example B in (b).

shown in Fig. 10(b), the auditory saliency map obtained from the proposed framework is robust to the strong background noise. It contains clear and correct saliency detection results which accurately represent the auditory saliency property of the original salient sounds in both spectral and temporal domain.

Moreover, it is shown from the experimental results that the accuracy and robustness of Kayser's approach will decrease sharply when the background noise is relatively strong and overlaps the salient sounds. Especially the short term salient sounds cannot be correctly detected when the acoustic background is

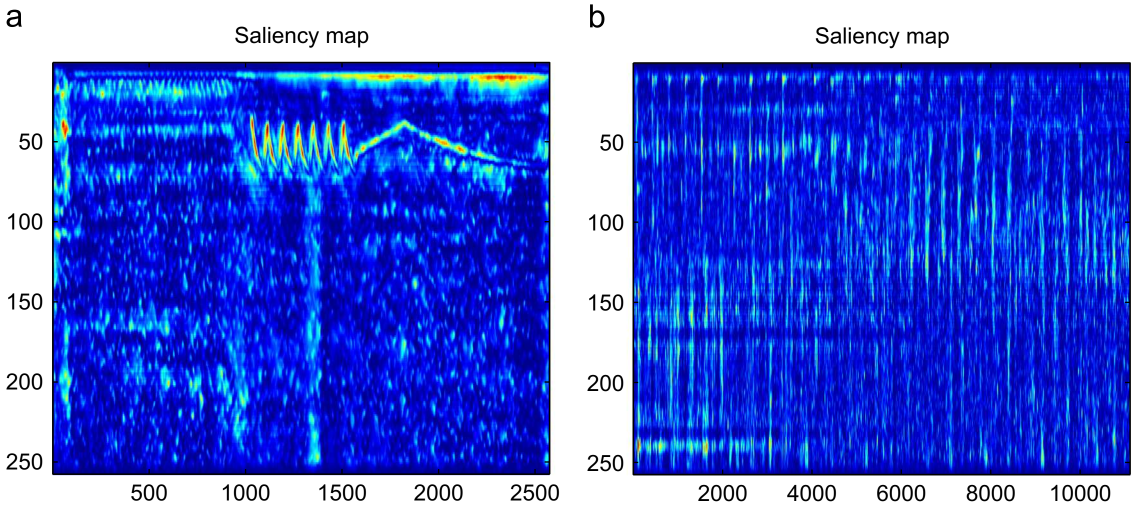

Fig. 11. The auditory saliency map based on Kayser's approach [12] of experiment sound example A in (a) and example B in (b).

composed of salient sounds as well. The explanation of this drawback to a large extent is that, the auditory saliency model of conventional approach is mainly based on the local spatiotemporal contrast and little global saliency information has been taken into account. Therefore, other previously mentioned auditory saliency models which based on the similar saliency detection principle could also confront the same limitation.

6. Conclusion

In this paper, motivated by the bio-inspired saliency detection mechanism of both human hearing and visual system, a novel salient environment sound detection framework for machine awareness is proposed. The proposed method is based on the combination of heterogeneous saliency features: (1) acoustic saliency feature which represented by MFCC in temporal domain and the PSD of sound in spectral domain; (2) visual saliency feature from spectrogram which transform auditory saliency into image saliency.

The contributions of the proposed method are as follows: (1) To provide a global saliency feature for detection and overcome the drawback of using local contrast, a short-term Shannon entropy (SSE) method is proposed to estimate the global saliency property; (2) to decrease the influence of background noise as well as the pseudo background noise that generated by less salient sounds, inspired by the researches of neurobiology that inhibitory effect exists when two salient points are close to each other, a computational IOR model is proposed to verify the temporal saliency derived from MFCC; (3) to accurately detect the salient sounds in auditory saliency map, a spectral saliency detection approach is presented to obtain the saliency feature from the PSD of sound signal; (4) the image saliency feature is achieved by using the opponent color space, the goal of which is to detect the salient sounds with high power energy represented by red color region, as well as the acoustic background with green color region in a log-scale spectrogram. The final saliency detection result is obtained by using a heterogeneous saliency feature fusion method and is given in the form of conventional saliency map.

Experiment results show that, the proposed framework has a significant improvement in processing real environment sound tracks. Especially in dealing with the sounds with strong level of background noise and overlapped salient sounds, real salient point can be correctly detected by applying the proposed inhibition of return (IOR) model. It has also indicated that, the inhibitory effect could influence the computation of auditory saliency detection and the importance of depressing the pseudo background noise which cause by less salient sounds. The final auditory saliency maps show the accuracy as well as the robustness, which can support that the proposed framework outperforms other conventional auditory saliency detection approaches.

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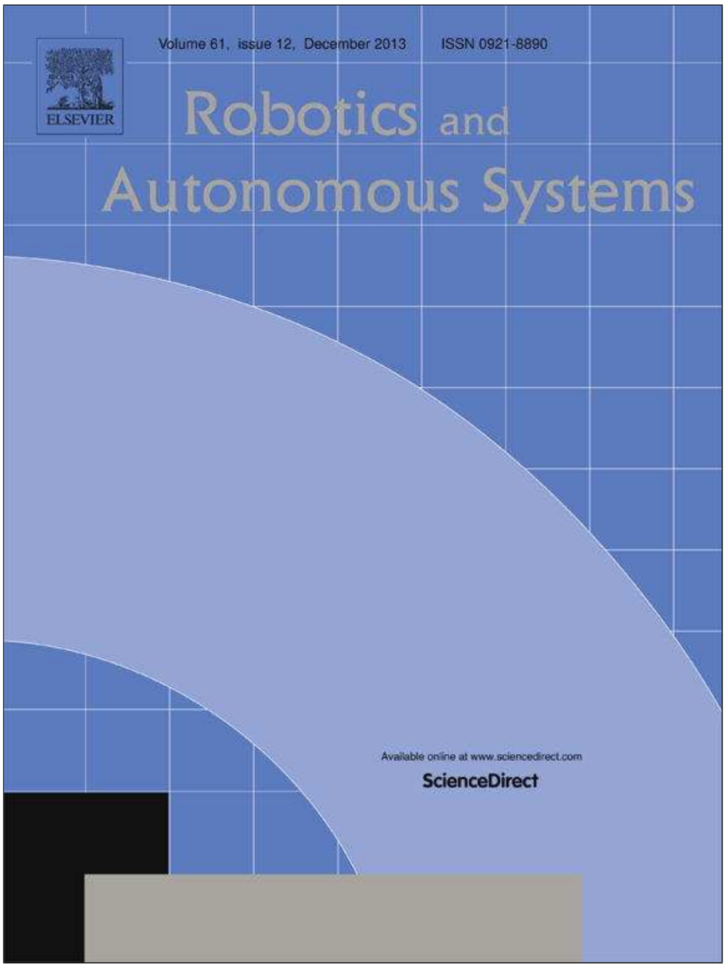
Autonomous knowledge acquisition based on artificial curiosity : Application to mobile robots in an indoor environment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Autonomous knowledge acquisition based on artificial curiosity: Application to mobile robots in an indoor environment

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HIGHLIGHTS

- Autonomous knowledge acquisition for mobile robots in a real environment.
- An artificial cognitive system based on perceptual and epistemic curiosity.
- Experimental results on a humanoid robot in a real office environment.

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ABSTRACT

This paper describes an autonomous system for knowledge acquisition based on artificial curiosity. The proposed approach allows a humanoid robot to discover, in an indoor environment, the world in which it evolves, and to learn autonomously new knowledge about it. The learning process is accomplished by observation and by interaction with a human tutor, based on a cognitive architecture with two levels. Experimental results of deployment of this system on a humanoid robot in a real office environment are provided. We show that our cognitive system allows a humanoid robot to gain increased autonomy in matters of knowledge acquisition.

1. Introduction

Nowadays there exist many systems, such as sensors or robotic bodies, that outperform human capacities. For example, in some manufactories, robotic arms are used to assemble complex systems. These robotic systems may carry out repetitive tasks more precisely and more quickly than humans. But contrary to robotic arms which can outperform human abilities, the humanoid robots (a significant example of application could be companion robots) are very sophisticated machines, but are still far to surpass the human abilities. In this case, a foremost problem to solve is to proffer autonomy to the robot because generally robots are able to carry out planified tasks when context is known, but yet none of the existing machines can be called truly "intelligent" and autonomous: in fact, sharing everyday life with humans is still far away. It is so because contemporary machines are often automatic as in the case of robotic arms, but rarely fully autonomous in their knowledge acquisition.

In recent years, there has been a substantial progress in robotic systems able to robustly recognize objects in the real world using a large database of pre-collected knowledge (see [1] for a notable example). There has been, however, comparatively less advance in autonomous acquisition of such knowledge. In fact, if an autonomous robot is required to learn to share the living space with its human counterparts and to reason about it in human terms, it has to face at least two important challenges. The first comes from the world itself, where there are a vast number of objects and situations that the robot may encounter in this real world. The other one comes from humans: it is the richness of the ways that we use to address those objects or situations using natural language. Moreover, the way we perceive the world and speak about it is strongly culturally dependent. It is shown e.g. in [2] regarding usage of color terms by different people around the world, or in [3] regarding cultural differences in description of spatial relations. A fully autonomous robot, that is supposed to respond correctly to those challenges, cannot rely solely on a priori knowledge that has been given to it by a human expert. On the contrary, it should be able to learn on-line, in the place where it is used and by interaction with the people it encounters there. On this subject, the reader may refer to [4] for a monograph on knowledge

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acquisition strategies, to [5] for a survey on human–robot interaction and learning and to [6] for an overview of the problem of anchoring.[1] This learning should be completely autonomous, but still able to benefit from interaction with humans in order to acquire their way of describing the world. This will inherently require that the robot has the ability of learning without an explicit negative evidence or negative training set and from a relatively small number of samples. While this important capacity is observed in children learning a language[2] (see e.g. [7]), the problem is a general one. For instance, when a child learns to recognize the color red, he does not need to know what is not red. The problem of autonomous learning has been addressed on different degrees in previous works. For example, in [8] a computational model of word-meaning acquisition by interaction is presented. The work also discusses the problem of word-meaning acquisition in young children. In [9] authors present a computational model for acquisition of a lexicon describing simple objects. The model is verified in a population of humanoid robots. While it does not directly aim to learn by interaction with humans, it shows an interesting approach to autonomous forming of concepts in robots. On the other hand the work is interesting because it shows how knowledge propagates in the population of robots in a way much resembling to what is happening in similar populations of humans. It would be very appealing to use the concepts proposed in the mentioned work to apply them on a mixed human–robot community using human language and to observe sharing of human knowledge with robots. In [10], a humanoid robot is taught by a human tutor to associate simple shapes to human lexicon in an interactive way. The interactive learning is explored also in [11], where a robot is required to learn to distinguish two classes of objects. In [12], a humanoid robot is taught through a dialog with untrained user with the aim to learn different objects and to grasp them properly. When robot learning is mediated through human–robot interaction, identification (verbal or nonverbal) of the referred-to objects is very important. See [13] for a recent contribution on joint attention in human–robot dialogs. In the work of [14], a lexical acquisition model is presented combining more traditional approaches with the concept of curiosity to alternate the attention of the learning robot. A more advanced work on autonomous robot learning using a weak form of interaction with the tutor has been recently presented in [15]. Its authors propose an online algorithm allowing a robot to perform multimodal categorization of objects with limited verbal input from human. Another interesting approach to autonomous learning of visual concepts in robots has been published in [16] where the authors show capacity of their robotic platform to engage in different kinds of learning in interaction with a human tutor. The latter two mentioned works are to date perhaps the most advanced examples of autonomous acquisition of knowledge by observation and interaction in embodied agents, i.e. humanoid robots.

Cognitive systems are autonomous systems that can perceive its environment, learn from experience, anticipate the outcome of events, act to pursue goals, and adapt to changing circumstances. A survey of artificial cognitive systems can be found in [17,18]. But, in the field of cognitive systems, two important questions are "Why do they do this?" and "How do they do it?" [19]. In this paper, we propose a new bio-inspired cognitive system which is based on an artificial curiosity. Our cognitive system allows an embodied agent (a humanoid robot in our case) to learn to interpret the world, in which it evolves, using appropriate terms from human language, while not making use of a priori knowledge. This cognitive system is based on two levels. The first level is done with a system allowing an autonomous detection and learning objects by means of visual saliency. The second level is carried out by interaction with humans to learn new knowledge. The term cognitive system means here specifically that characteristics of such a system are similar to those of human cognitive system. It refers the reader to the fact that a cognitive system, which would be able to comprehend the world on its own, but whose comprehension would be non-human, would subsequently be incapable of communicating about it with its human counterparts. For example, to describe the colors of an object, humans use natural language (words as blue or red) rather than numerical values generally used in computing systems. Moreover, human language (blue, red, etc.) may be culturally dependent. Concerning the use of curiosity in machine cognitive systems, by observing the state of the art it may be concluded that curiosity is usually used as an auxiliary, single-purpose mechanism, instead of being the fundamental basis of the knowledge acquisition. To our best knowledge there is no work to date which considers curiosity in context of machine cognition as a drive for knowledge acquisition on both low (perceptual) level and high (semantic) level of the system, as it is done in this article. In short, our model is closely inspired by the learning behavior of human infants (see e.g [20–22]). The goal of this system is to allow to an autonomous robot to anchor the heard terms during its sensorimotor experiences, and to flexibly, to shape this anchoring according to its growing knowledge about the world. Furthermore, the robot is able to decide itself to interact with a human in order to complete its knowledge.

The common thread of this work is the curiosity and the paper gives two main contributions. The first is to provide a full concept which proves that a robot is able to acquire new knowledge based on curiosity. The second contribution is to describe precisely a method which show how a robot can interpret the world by using its observations and beliefs. This article is further organized as follows. Section 2 explains theoretical aspects of the present cognitive system and namely the role of curiosity. Section 3 briefly recounts important aspects of the lower cognitive level of the discussed system, relying on our previously published work. Section 4 details on the higher cognitive level. The experimental framework is given in Section 5. Section 6 shows results about its application in real world. Finally Section 7 discusses the achieved results and the future work.

2. Artificial curiosity and autonomous knowledge acquisition

Curiosity is an important factor both for human cognition and for the conception of artificial systems that need gathering knowledge autonomously. To explain this affirmation, we will focus on curiosity in more depth. In Section 2.1, we will discuss the foundations of the proposed approach. Sections 2.2 and 2.3 will focus on perceptual curiosity and epistemic curiosity respectively.

2.1. Role of curiosity

In the introduction to his "Theory of human curiosity", Berlyne [23] said that for humans curiosity is a source of stimulation to acquire new knowledge. In this work, the author proposes splitting up curiosity into two kinds. The first one is so-called "perceptual curiosity", which leads to increased perception of stimuli. It is a lower level function, more related to perception of new, surprising or unusual sensory input. It contrasts to repetitive or monotonous perceptual experience. The other one is called "epistemic curiosity", which is more related to the "desire for knowledge that motivates individuals to learn new ideas, eliminate information-gaps, and solve intellectual problems" [24].

[1] Anchoring is the problem of connecting, inside an artificial system, symbols and sensor data that refer to the same physical objects in the external world (see [6]).

[2] Researchers in child language acquisition have often observed that the child learns language apparently without the benefit of negative evidence.

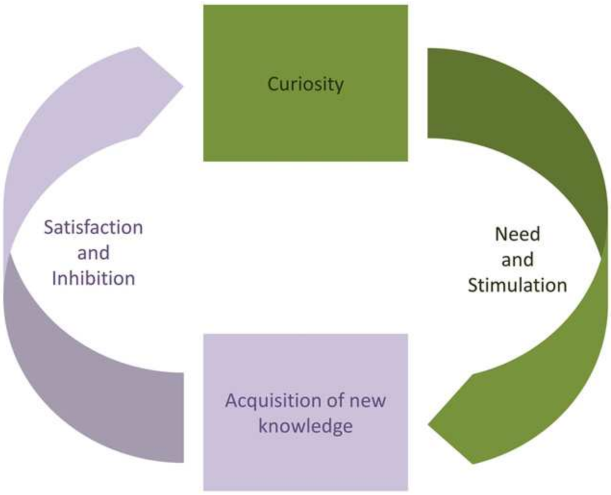

Fig. 1. Diagram of the role of curiosity in stimulation of new knowledge acquisition in a cognitive system.

It also seems that it acts to stimulate long-term memory in remembering new or surprising information [25]. Without striving for biological plausibility, what has been previously said about curiosity gives an important biological motivation for building of our system. On Fig. 1, a diagram is shown, which depicts the way in which curiosity stimulates acquisition of new knowledge and in turn the newly learned knowledge appeases or inhibits curiosity. We adopt this as the basic working scheme for the envisaged system. By consequence, it is curiosity, which motivates any action of the system.

In conformity with the aforementioned concept about the two kinds of curiosity, i.e. "perceptual curiosity" and "epistemic curiosity", we break down the process in two stages in order to capture the role of both kinds of curiosity. This is shown on Fig. 2. On the left hand side of the figure, sample sensory data (an image) is shown. On this data perceptual curiosity motivates or stimulates what we call the low level knowledge acquisition. It seeks "surprising" or "attention-drawing" information in given sensory data and thus devises of it a low-level knowledge. The task of perceptual curiosity is realized by perceptual saliency detection mechanisms (see further in Section 3). This gives the basis for operation of high level knowledge acquisition, which is stimulated by epistemic curiosity. Being previously defined as the process that motivates to learn new ideas, eliminate information-gaps, and solve intellectual problems, epistemic curiosity is here the motor of (a) learning new concepts based on what has been gathered on the lower-level and (b) eliminating information gaps by encouraging an active search for the missing information (see further in Section 4). Finally, this high-level (semantic) knowledge is stored and used when needed.

2.2. Perceptual curiosity realization through perceptual saliency

In their perception, humans rely strikingly much on vision. It is then only pertinent to consider chiefly the visual information and learning processes connected to it. Following the scheme from Fig. 2, this is the place, where perceptual curiosity is realized through a perceptual saliency detection approach. It appears appropriate here to draw inspiration from studies on human infants and robots learning by demonstration. Experiments in [22] show that it is the explicitness or exaggeration of an action that helps a child to understand, what is important in the actual context of learning. It may be generalized, that it is the saliency (in terms of motion, colors, etc.) that lets the pertinent information "stand-out" from the context [26] and become "surprising". This is supported by a number of existing works. For example in [27], the authors are convinced that important variations in the input sensory signal make the child distinguish the pertinent information from the informational background. Similarly, experiments conducted in [22] show, that it is the explicitness or certain exaggeration of an action or presented information (in terms of voice, movement, color, etc.) that helps a child to understand what is significant in the actual context of learning and what is unimportant. We argue that in this context the visual saliency may be helpful to enable unsupervised extraction and subsequent learning of a previously unknown object by a machine in a way that realizes perceptual curiosity. The present low-level knowledge acquisition approach is inspired by human vision system and by existing research on juvenile human (infants) learning process. The proposed approach extracts, first, objects of interest by means of visual saliency and secondly categorizes those objects using such acquired data for learning, which may be identified as an unconscious cognitive function. Then a conscious cognitive function is realized, on a higher level, by an intentional acquisition of new knowledge and seeking to fill informational gaps. This is discussed in the following sub-section.

2.3. Epistemic curiosity realization through learning by observation and by interaction with humans

The high level knowledge acquisition mechanism is stimulated by epistemic curiosity in order to produce new semantic knowledge and to fill the gaps of missing knowledge. Contrary to the previously described perceptual curiosity apparatus, which is performed in an "unconscious" manner, the realization of epistemic curiosity is inherently a "conscious" cognitive function, as it requires an intentional search and interaction with the environment. The mechanism allows an embodied agent (e.g. a humanoid robot) to learn to interpret the world, in which it evolves, using appropriate terms from human language. It is important to stress that this is done without making use of a priori knowledge. The task is realized by word-meaning anchoring based on learning by observation and by interaction with its human tutor. The model is closely inspired by learning behavior of human infants (see e.g. [20] or [21]). The robot shares the world with a human tutor and interacts with him. The tutor on his turn shares with the robot his knowledge about the world in the form of natural speech (utterances), which accompany observations made by the robot. The described system can play a key role in linking existing object extraction and learning techniques (e.g. SIFT [28] matching or salient object extraction techniques) on one side, and ontologies on the other side. The former ones are closely related to perceptual reality, but are unaware of the meaning of objects they are treated, while the latter ones are able to represent complex semantic knowledge about the world, but, they are unaware of the perceptual reality of concepts, which they are handling.

3. Autonomous detection and learning objects by means of visual saliency

As the realization of perceptual curiosity has been identified with the perceptual (especially visual) saliency, we will focus in this section on an autonomous visual saliency based technique for object detection and learning.

In the past decade, the scientific community has witnessed great advance in the field of techniques for object detection and recognition, such as SIFT [28], SURF [29], Viola–Jones detection framework [30], color co-occurrence histograms [31], to mention only a few. While these methods show often high rates of recognition and are able to operate in real time, they all rely on human made databases of manually segmented or labeled images containing the object of interest without extensive spurious information

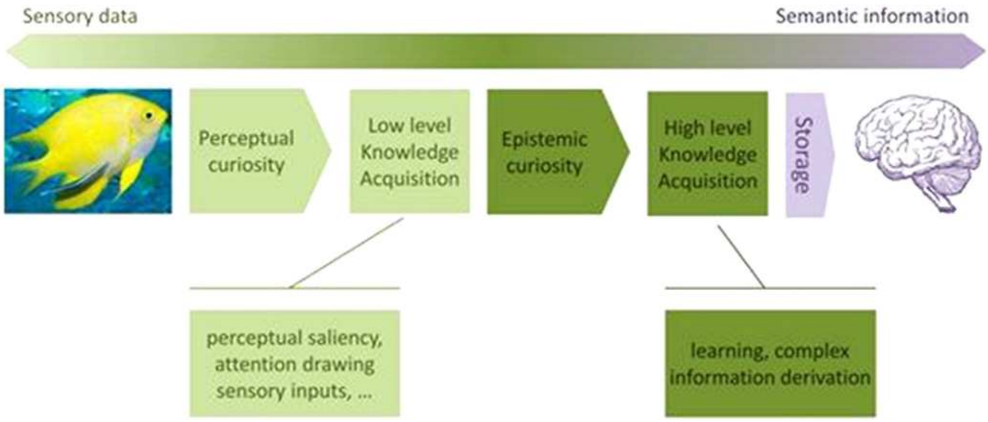

Fig. 2. The place of perceptual and epistemic curiosity in learning of complex knowledge from raw sensory data.

and background. The mentioned database is sine qua non for a successful recognition process, but its manual creation often requires a considerable time and a skilled human expert. This impedes design of a fully autonomous machine vision system, which would learn to recognize new objects on its own.

Motivated by the mentioned shortcoming regarding existing object recognition methods, we have proposed earlier an intelligent machine vision system able to learn autonomously individual objects present in real the environment. The approach has been detailed in [32,33]. Its key capacities are the following ones:

- Autonomous extraction of multiple objects from raw unlabeled camera images,
- Learning of those objects autonomously without human intervention,
- Recognition of the learned objects in different conditions or visual contexts.

The goal for this system is to allow an embodied agent, e.g. a humanoid robot to learn to recognize objects encountered in its environment in a completely autonomous manner. The system itself is however not limited to mobile platforms and it can be very well used in context of sensor networks, intelligent houses etc. With respect to this envisaged goal, the system is designed with emphasis on on-line and real-time operation and we have validated it on a color camera equipped mobile robot in an explore and learn task performed in a real-world office environment. The mentioned object learning system consists of several units which collaborate together.

On Fig. 3 a block-diagram of the system is depicted showing the individual units and their relations. Two main parts may be identified. The first one, labeled "Acquisition of new objects for learning" takes a raw image from the camera, detects visually important objects on it and extracts them so that they can be used as prospective samples for learning. Each one of the two mentioned parts contains several processing units. In the first unit, as a new image is acquired by the camera, it is processed by the "Salient region detection" unit. Here, using features of chromaticity and luminosity along with local features of center-surround histogram calculation, a saliency map is constructed. It highlights regions of the image that are visually important, i.e. that are visually more salient with respect to the rest of the image. In parallel the input image is processed in the "Fast image segmentation", which splits the image into a set of segments according to the chromatic surface properties. The algorithm is shown to be robust to common illumination effects like shadows and reflections, which helps our system to cope with real illumination conditions. Finally the "Salient object extraction" unit combines results of the two previous, extracting the segments found on regions that exhibit significant saliency and forming them together to present at the end salient objects extracted from the input image. As images are taken consecutively by the camera, salient objects extracted from each one are fed into the "Incremental fragment grouping" unit. Here, an on-line classification is performed on each object by a set of weak classifiers and incrementally groups containing the same object extracted from different images are formed. These groups can be then used as a kind of visual memory of visual database describing each of the extracted objects. This alone could be enough for recognition of each of the objects, if it was ensured that each particular object will be found in the same visual context (i.e. in the context where the object is salient with respect to its surroundings) next time it is encountered by our system. This is clearly too restrictive for a system with a goal to recognize the once learned objects in any conditions. That is why the last unit of the system, tagged "Object recognition methods", is added. Its role is, by employing existing object recognition algorithms, to learn from the visual database built by "Incremental fragment grouping" unit and to recognize those objects regardless to their saliency in new settings. Thus for once learned objects, they can be recognized directly on the input image, which is denoted by the very bottom arrow on the Fig. 3 labeled "Direct detection of already learned objects".

4. Knowledge acquisition from observation

In this section, we detail our approach to autonomous high-level knowledge acquisition. This represents the high level, epistemic curiosity driven knowledge acquisition process discussed in Section 2.3. First we outline its general principles concerning learning of a single type of features at one time. Then we explicate how beliefs about the world are generated by the robot based on its autonomous observations of the world and on its interaction with a human tutor. Then we detail on how the robot uses those beliefs to interpret the environment in which it evolves.

4.1. General overview of the system

The problem of learning brings an inherent problem of distinguishing the pertinent sensory information (the one to which the tutor is referring) and the impertinent one because sensors provide more data than is necessary. It is the task of higher structures (e.g. an attention system or in general a machine learning system adapted to this task) to draw the attention to particular features of the data, which are pertinent in context of a particular task. This problem has been addressed by researchers in different fields (for a reference, see e.g. [34] or [35]). The solution to this task is not obvious even if we achieve joint attention in the robot. This is illustrated

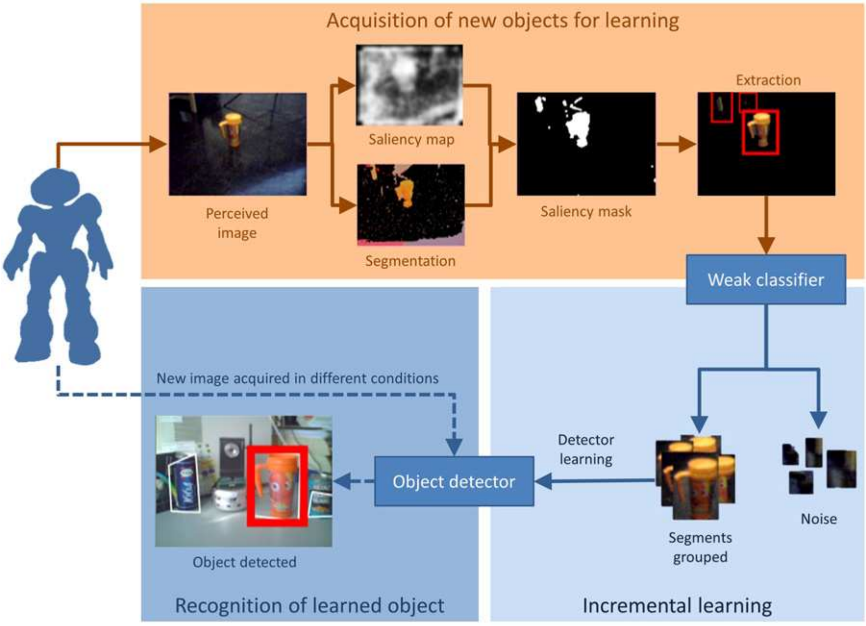

Fig. 3. Overview of the entire proposed system's work-flow. An unknown object is incrementally learned by extracting it and providing it as learning samples to the object detector (solid arrows). This enables recognition of the object when encountered again (the dotted arrow).

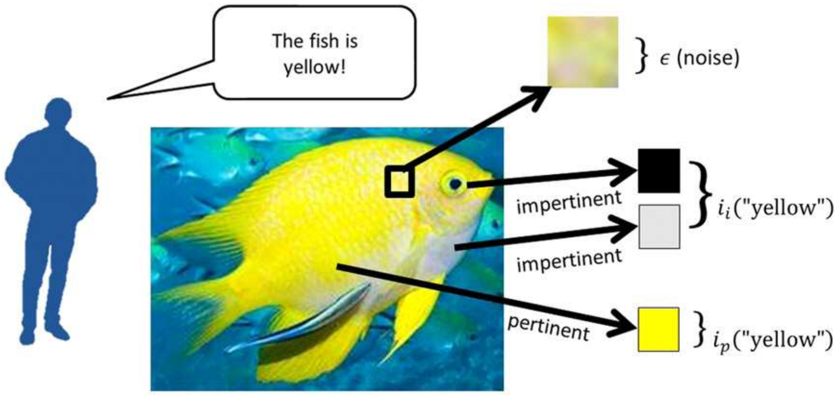

Fig. 4. A human would describe this fish as being yellow in spite of the fact, that this is not by far its only color (symbols i_i and i_p refer to Eq. (1)). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

on Fig. 4. Consider a robot learning a single type of features, e.g. colors. If a tutor points to one object (e.g. a yellow fish) among many others, and describes it by saying "The fish is yellow!" the robot still has to distinguish, which of the several colors and shades found on the object the tutor is referring to. This step is an inevitable one before we can proceed to the learning itself. In traditional learning systems, this task-relevant (i.e. pertinent) information is extracted by hand by a human expert. In a system capable of autonomous learning, however, this has to be done in an autonomous way and without recourse to human-extracted features.

To achieve correct detection of pertinent information in spite of such an uncertainty, we adopt the following strategy (see also Fig. 5). The robot extracts features (I_l) from important objects found in the scene along with words the tutor used to describe the presented objects. Then, the robot generates its beliefs about which word could describe which feature. The beliefs are used as organisms in a genetic algorithm. The utterances pronounced by the human tutor in presence of each such object are compared with the utterances the robot would use to describe it based on the current belief. The closer the robot's description is to the one given by the human, the higher the fitness is. To calculate the fitness, a classifier is trained based on each belief about the world. Using it, the cognitive system tries to interpret the objects the robot has already seen. Once the evolution has been finished, the belief with the highest fitness is adopted by the robot and is used to interpret occurrences of new (unseen) objects.

4.2. Observation and belief

Let us have a robot endowed with a sensor. The world is represented as a set of features[3] $I = \{i_1, \ldots, i_k\}$, which can be acquired by this sensor. Each time the robot makes an observation o, a human tutor gives him a set of utterances U_H describing important objects found currently in the world. For this purpose, let us define an observation o as an ordered pair $o = \{I_l, U_H\}$, where $I_l \subseteq I$ stands for the set of features obtained by observing the world and $U_H \subseteq U$ is a set of utterances given in the context of the observation. Let us denote the set of all utterances ever given about the world as U. The goal for the robot is to distinguish the pertinent

3 In the proposed example, features are the components of the color modeling (siRGB). But it must be noticed it is possible to use others approaches like RGB or YCbCr.

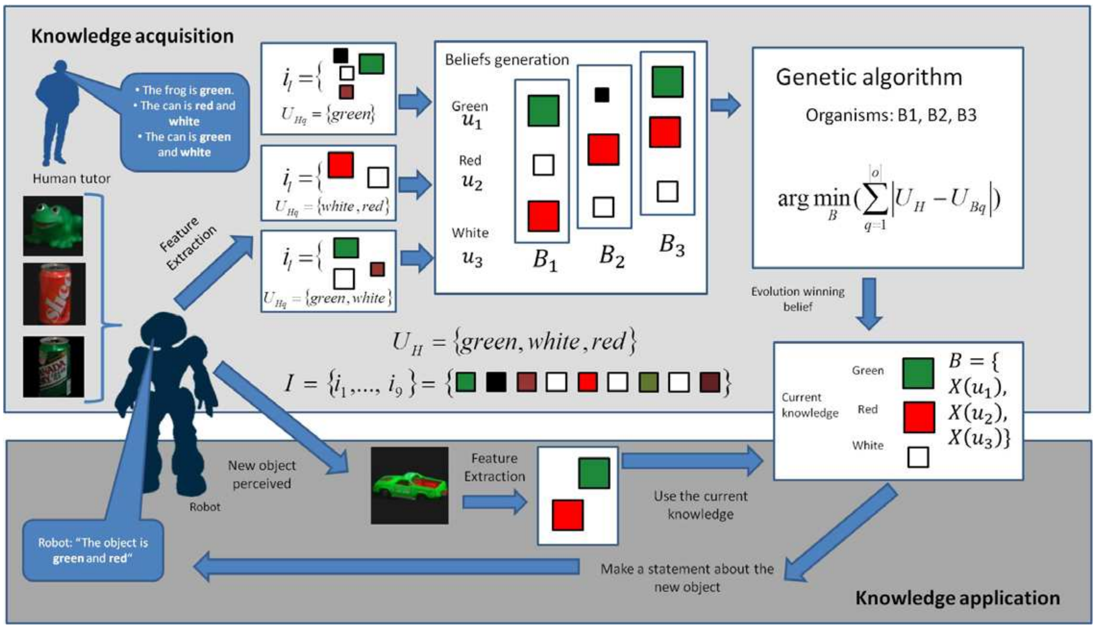

Fig. 5. Graphical depiction of the proposed system for learning a single type of features. For the sake of comprehensibility it is shown in context of a particular learning task, i.e. color learning, instead of a purely symbolic description. The robot does three observations: $o_1 = \{i_1, i_2, i_3, i_4, green\}$, $o_2 = \{i_5, i_6, white, red\}$ and $o_3 = \{i_7, i_8, i_9, green, white\}$. After the learning process, the robot is able to deduce that the car is red and green. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

information[4] (i_p) present in the observation o from the impertinent one (i_i) and to correctly map the utterances (U_H) to appropriate perceived stimuli (features). Fig. 5 illustrates the acquisition process. In this example, the robot makes three observation where each observation is composed of several features and one or two utterances ($o_1 = \{i_1, i_2, i_3, i_4, green\}$, $o_2 = \{i_5, i_6, white, red\}$ and $o_3 = \{i_7, i_8, i_9, green, white\}$). In each of these observations, the robot perceives the both pertinent and impertinent information. For instance, in the first observation (the frog), the robot perceives four main features, but there is only one pertinent feature which correspond to the color green. If the robot makes only one observation, it is not able to anchor the utterance green with the feature green. In other words, the robot is required to establish a word-meaning relationship between the uttered words and its own perception. But the robot is further allowed to interact with the human in order to clarify and verify (e.g. by making new observations) its interpretations.

Following Eq. (1), I_l is a sum of all the pertinent information i_p for a given u (i.e. features that can be described as u in the language used for communication between the human and the robot), all the impertinent information i_i (i.e. features that are not described by the given u, but might be described by another $u_i \in U$) and sensor noise ϵ.

$$I_l = \bigcup i_p(u) + \bigcup i_i(u) + \epsilon. \tag{1}$$

Let us define an interpretation $X(u)$ of an utterance u as an ordered pair $X(u) = \{u, I_j \subseteq I\}$, which denotes that a set of features I_j from all the features I of the world is interpreted as u ($X(green) = \{green, i_1, i_7\}$). Then we define a belief $B = \{X(u_1), \ldots, X(u_n); n = |U|\}$ as an ordered set of $X(u)$ interpreting all utterances u from U ($B = \{X(green), X(white), X(red)\}$).

Now, according to Eq. (2), we can calculate the belief B, which interprets in the best way the observations made so far. It is done by looking for such a belief, which minimizes across all the observations $o_q \in O$ the difference between the utterances U_{Hq} made on each particular observation by human, and the utterances U_{Bq} that the robot may do using its beliefs B relating the observed situation. In other words, we are looking for a belief B allowing to the robot to describe a particular scene with the same utterances as a human on this same scene.

$$\arg\min_B \left(\sum_{q=1}^{|O|} \left| U_{Hq} - U_{Bq} \right| \right). \tag{2}$$

4.3. Belief generation

The system has to look for a belief B, which would make the robot describing a particular scene with utterances as close and as coherent as possible to those made by a human on the same scene. For this purpose, instead performing the exhaustive search over all possible beliefs, we propose to search for a suboptimal belief by means of a genetic algorithm. For doing that, we assume that each organism within it has its genome constituted by a belief, which, results into genomes of equal size $|U|$ containing interpretations $X(u)$ of all utterances from U. Let us have a belief generation process to generate genomes of organisms for the genetic algorithm as follows. For each interpretation $X(u)$ let us go through the entire set O of observations made. For each observation $o_q \in O$, if $u \in U_{Hq}$ then features $i_q \in I_j$ (with $I_j \subseteq I$) are extracted. This set of features, as described in Eq. (1), contains pertinent and impertinent features (with respect to current u) and noise. The task of coherent belief generation is to generate beliefs, which are coherent with the observed reality. This is done by deciding, which features $i_q \in I_j$ (with I_j may possibly the pertinent ones). The decision is driven by two principles. The first one is the principle of proximity.[5] As it is well known, similar things are more likely to

[4] For the shake of clarity, we consider on the example of Fig. 4 only one feature for the color yellow. But it must be pointed out, there may be several pertinent information when the color is inhomogeneous.

[5] In our case, the proximity may be evaluated by the distance between two points in the siRGB space.

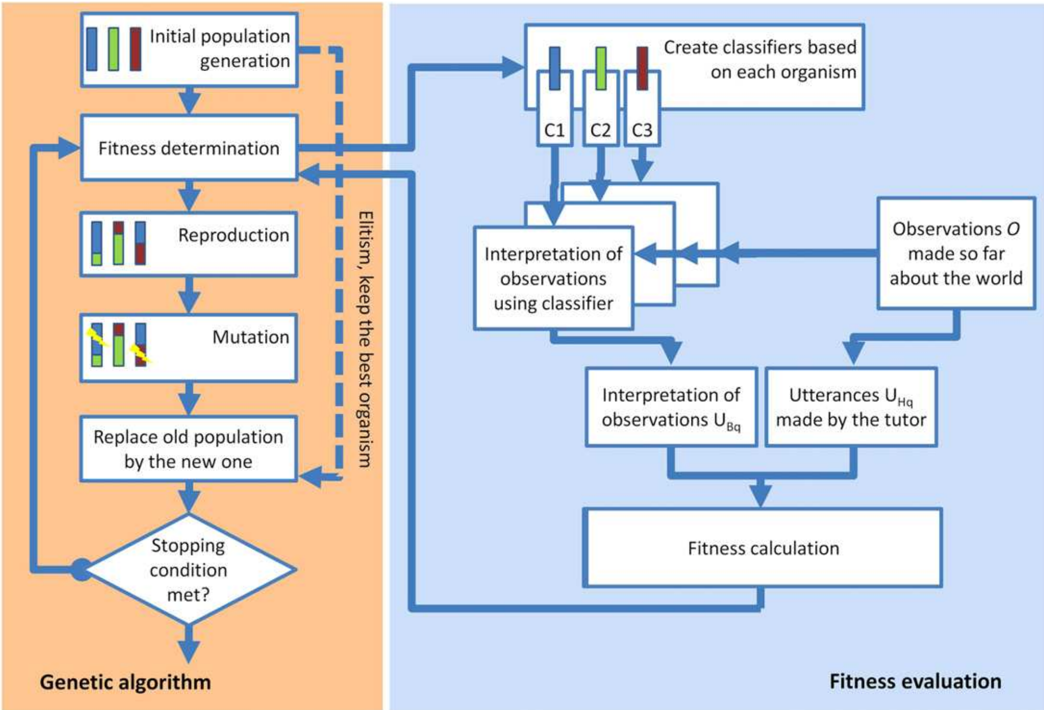

Fig. 6. Graphical depiction of genetic algorithm workflow. The left part describes the genetic algorithm itself, while the right part focuses on the fitness evaluation workflow.

be called the same name, than those less similar. As an application of it, any feature i is more likely to be selected to be pertinent in the context of u, if its distance to other features already selected is comparatively small. The second factor is the coherence with all the observations in O. This means, that any observation $o_q \in O$, where $u \in U_{Hq}$, has to have at least one feature i assigned into I_j of the current $X(u) = \{u, I_j\}$. Thus, it is both the similarity of features and the combination of certain utterances with certain features in observations from O, that guide the belief generation process. These beliefs may be perceived as "informed guesses" on the interpretation of the world made by the robot. The algorithm to generate coherent belief is given in Appendix A.

4.4. Evolution and best interpretation search

In the previous section, we have defined an approach for generation of coherent beliefs about the world, which are coherent with existing observations. Each of these beliefs makes one organism, which is used inside a genetic algorithm (see Fig. 6). In this work, we are mostly using an extended notion of genetic algorithm. Contrary to [36], in our work genomes are not composed of a series of bits (0 or 1), but are rather represented by chains of real numbers or complex objects. Nonetheless, the scheme of operation of the genetic algorithm remains the same.

Here, we define the fitness function by Eq. (3). To evaluate a given organism, we train normal Bayes classifier,[6] whose classes are the utterances from U and training data for each class u are given by $X(u) = \{u, I_j\}$, i.e. the features associated with the given u in the genome. This classifier is used through whole set O of observations, classifying utterances $u \in U$ describing each $o_q \in O$ accordingly to its extracted features. Such classification results in the set of utterances U_{Bq} (meaning that a belief B is tested regarding the qth observation). The fitness function evaluating the fitness of each above-mentioned organism is defined as "disparity" between U_{Bq} and U_{Hq} (defined in previous sub-section) which is computed accordingly to the Eq. (3) where v is the number of utterances that are not present in both sets U_{Bq} and U_{Hq} (e.g. either missed or are superfluous utterance interpreting the given features). The globally best fitting organism is chosen as the belief that best explains observations O made by the robot.

$$D(v) = \frac{1}{1+v} \quad \text{with } v = \left|U_{Hq} \bigcup U_{Bq}\right| - \left|U_{Hq} \bigcap U_{Bq}\right|. \qquad (3)$$

At the end of the evolution, we chose the globally best fitting organism as the belief that best explains observations O made so far about the world.

4.5. Human–robot interaction during learning

As shown in works from domains of linguistics and psychology (see e.g. [21]), language is not a mere static set of "tags", that we give to entities of the world around us, but it is a dynamic system, which influences perception and which is at the same time influenced by perception. Another important remark is, that human beings learn both by observation and by interaction with the world and with other human beings. The former is captured in our system in the "best interpretation search". It is a state resembling human infants in pre-lingual age. The latter type of learning requires that the robot is able to communicate with its environment (as it is a case for a child with developed speech capabilities) and is facilitated by previous learning by observation, which may serve as its bootstrap. In the present approach, this learning by interaction is carried out in two manners implying two directions: human-to-robot and robot-to-human.

Let us have a robot co-operating with its human counterpart. The first manner (human-to-robot) is employed anytime the robot interprets wrongly the world (due to incomplete knowledge about it, e.g. by bringing a "purple" mug when asked for a "red" one, provided that it has never encountered a "purple" thing before and thus it interprets it as a "red" one). If the human sees this wrong response, he provides the robot a new observation by uttering the desired interpretation ("purple" in our example) in presence of the

6 http://www.emgu.com/wiki/index.php/Normal_Bayes_Classifier_in_CSharp.

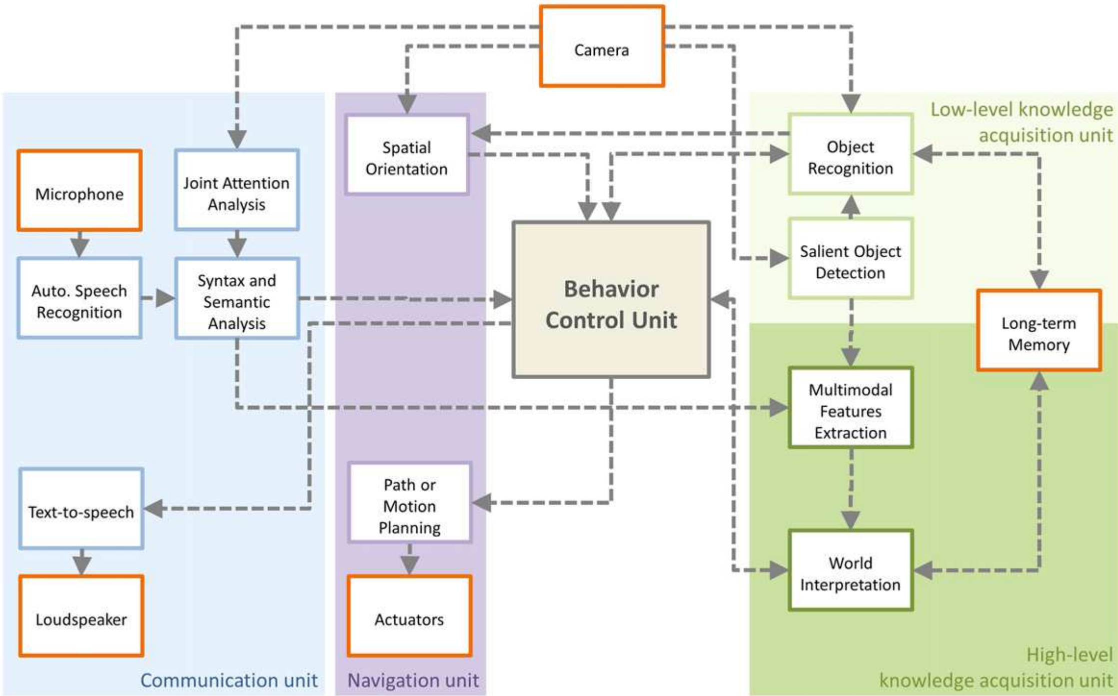

Fig. 7. Composition of the entire system in deployment. Each box corresponds to a processing unit described in Section 5.1.

wrongly interpreted features (i.e. the purple mug). The robot takes this new, corrective, knowledge about the world into account and searches for a new interpretation of the world, which would be conform with this new observation. The second manner (robot-to-human) may be employed when the robot attempts to interpret a particular feature. If the classifier trained with the current belief classifies the given feature with a very low confidence, this may be a sign, that this feature is a borderline example. In this case, it may be beneficial to clarify its true nature. The Appendix B describe an algorithm to detect ambiguities in a set of utterances. Thus, the robot asks its human counterpart to make an utterance about the observation in question. If the robot's interpretation does not conform with the utterance given by the human (robot's interpretation was wrong), this observation is recorded as a new knowledge and a search for the new interpretation of the world is started as in the previous case. Using these two ways of interactive learning, the robot's interpretation of the world evolves both in quantity, covering increasingly more phenomena as they are encountered, and in quality, shaping the meaning of words (utterances) to conform with the perceived world.

5. Experimental framework

In Section 2, a theoretical basis of our approach to autonomous acquisition of knowledge has been outlined and its concept has been presented. Through Sections 3 and 4 solutions have been proposed to different aspects of this concept. In this section we are going to bring all the previously mentioned parts together in one functioning system and we will describe its application in the framework of companion robot. In few years, we believe that companion robots (e.g. small humanoid robot), progressively, will share with human the same environment. Consequently, it is very important to prove that it is possible to improve capabilities of this kind of robots. Thus, this section is meant to provide an all-in-one realization description of the entire system and to show how it contributes to investigate the above-mentioned foremost problem of fully autonomous knowledge acquisition capabilities in a robot. In this context, we think the NAO humanoid robot is well adapted for our experimental validation because:

- First, the robot NAO and the associated software give an excellent framework to validate new strategies allowing improving autonomy of future robots.
- Second, the functionalities (e.g. motion, vision, speech) of this small humanoid robot are very similar to the abilities needed (e.g. expected to be available) to companion robots.

Section 5.1 gives an overview of the control architecture. Because the interaction between human and robot (essentially verbal communication) plays a key role in our experiment, the Section 5.2 is now dedicated to give a detailed description of the used strategies.

5.1. Control architecture

The control architecture (see Fig. 7) is split into five main units (Communication Unit, Navigation Unit, Low-level Knowledge Acquisition Unit, High-level Knowledge Acquisition Unit, Behavior Control Unit):

- The Communication Unit has an output communication channel and an input communication channel. The output channel is composed of a Text-to-speech engine which generates human voice through Loudspeakers. It receives the text to say from the Behavior Control Unit. The input channel takes its input from a microphone and through an Automated Speech Recognition engine and the Syntax and Semantic analysis it provides the Behavior Control Unit labeled chain of strings representing the heard speech.
- The purpose of navigation unit is to allow the robot to position itself in space with respect to objects around it and to use this knowledge to navigate in the environment. Capacities needed in this context are obstacle avoidance and determination of distance to objects. Its sub-unit for Spatial Orientation takes its input from the camera and from the Object Recognition sub-unit from the Low-level Knowledge Acquisition Unit. To resolve the obstacle avoidance problem, we have adopted a technique based on ground color modeling. Color model of the ground

helps the robot to distinguish free-space from obstacles. The approach is loosely inspired by the work presented in [37]. The assumption is made that obstacles repose on ground (i.e. overhanging and floating objects are not taken into account). With this assumption the distance of obstacles can be inferred even from monocular camera data. In [38] some aspects of distance estimation from a static monocular camera have been mentioned. We have developed the approach presented there in order to give the robot the capacity to infer distances and sizes of surrounding objects.

- The Low-level Knowledge Acquisition Unit ensures gathering of knowledge on lower levels of semantics, such as detection of salient objects (by the Salient Object Detection sub-unit) and their learning and subsequent recognition (in the Object Recognition sub-unit). Those activities are carried out mostly in an "unconscious" manner, i.e. they are run as an automatism in "background" while collecting salient objects and learning them. The learned knowledge is stored in Long-term Memory for further use.
- The High-level Knowledge Acquisition Unit is the place where outputs from other units (prominently the Low-level Knowledge Acquisition Unit for its features output and the Communication Unit for its linguistic output) are combined together and where high-level semantic representation is derived from them. Unlike the Low-level Knowledge Acquisition Unit, this unit represents conscious and intentional cognitive activity much like a baby which learns from observation and from verbal interaction with adults about the world and develops in this way its own representation of the world.
- The Behavior Control Unit plays the role of a coordinator among other units of the system. It directs data flows and issues command signals for other units. Also, as its name suggests, it controls the behavior of the robot and alternates it in order to respond properly to external events.

  On Fig. 8 the Behavior Control Unit (BCU) operation is depicted in form of a flowchart. Some of the boxes of the flowchart are filled with colors corresponding to one of the four main units. This is to indicate that the particular unit is involved in the operation described by the box. The BCU operation starts with initialization of all the units and with starting of their proper operation cycle. Then, data about the environment from the Navigation unit is gathered and the robot starts moving through the environment in order to explore it. This could be considered "idling around" or free exploration and satisfying its own curiosity in moments when the robot has got no particular order. If a new object is found, the robot attempts to ask somebody about the object in order to learn more knowledge about it. This behavior cycle breaks when an input from the tutor is received, be it a response to a robots inquiry or the tutors proper intention to interact with the robot. Remember that the tutor could be any human willing to interact with the robot while possibly sharing his own knowledge. If a (vocal) input is received, the robot tries to resolve symbols used in the input. Consider the input stating "Can you tell me, what the red thing over there is?" The symbols used in the phrase would be "red", "thing over there". The BCU would receive an input from the High-level Knowledge Acquisition Unit saying the concept of "red" is already known, it would receive an input from the Communication Unit resolving the joint attention problem of "over there" and finally the Low-level Knowledge Acquisition Unit would say that the object is not yet in its long-term memory and thus it is unknown to it. At this stage, the symbol cannot be resolved and the BCU will initiate a behavior directed to get information about the unknown symbol (i.e. about "the red thing over there") possibly by asking somebody about it by saying "Please, tell me what is the name of this object". This "curious" behavior would also be initiated if all the symbols were resolved, but some of them without a sufficient certainty. Imagine the robot had seen very few red things so far and the concept of "red" was anchored with high uncertainty. In this case, the robot could engage in a behavior trying to refine its knowledge by asking "Sorry, I am unsure about what is red, could you show me some more objects that are red". Both behaviors described here are intended to drive the robot towards enriching and enhancing its knowledge about the world. If all symbols are known with a sufficient certainty, the input from the tutor is further processed. If it is an affirmative phrase, i.e. it contains a knowledge explicitly expressed like in the phrase "The book is heavy", it is extracted and the robots inner representation of the world is updated. If the phrase is a question, it is replied using symbols resolved earlier. If it is an order, it is executed. In case the type of phrase could not be decided (possibly a grammatically incorrect or incoherent phrase), the robot asks for a reformulation of the input. The same happens if the phrase is beyond the robots understanding, which would be most likely due to limited vocabulary or comprehension of the robot. When interaction is finished the BCU falls back to the free exploration behavior until new interaction is initiated from the side of the robot or of the tutor.

5.2. Human–robot interaction

For knowledge transfer between a human and a robot a suitable communication channel is necessary. The choice of verbal communication is obvious as it is arguably the most natural way for humans to share their thoughts and their knowledge. In order to enable verbal communication capabilities in a robot, there must be at least two requirements fulfilled: a hardware support present in the robot (i.e. microphones and loudspeakers) and a software support (a text-to-speech generator and automated speech recognition). In NAO robot both hardware components are present. For the software part, it is equipped by text-to-speech module and automated speech recognition developed by Nuance.[7] They are both exposed on NAOqi API.[8]

Another part of the problem of human–robot verbal communication is the understanding of what the human is saying. The product of speech recognition is a string containing words heard by the robot. To obtain the important information from the string, e.g. the subject and object of the phrase or the verb, a syntactic analysis is necessary. To perform syntax analysis, TreeTagger[9] tool is used. TreeTagger is a tool for annotating text with part-of-speech and lemma information. On Table 1 a simple English phrase is shown along with syntactic analysis output of TreeTagger in form of tokens. The "Part-of-speech" row gives tokens explanation and the "Lemma" row shows lemmas output, which is the neutral form of each word in the phrase. This information along with known grammatical rules for creation of English phrases may further serve to determine the nature of the phrase as declarative ("This is a box".), interrogative ("What is the name of this object?") or imperative ("Go to the office!"). It can be also used to extract the subject, the verb and other parts of speech, which are further processed in order to motivate the appropriate response action in the robot. Algorithms used by the TreeTagger tool are based on the work published in [39,40]. In this experimentation, you used only short sentences like "this an apple" for demonstrative framework, "the apple is red" for a descriptive phrase, or "Describe it?" for an order. Of course, the verbal interaction is restricted but it must be

7 http://www.nuance.com.

8 http://www.aldebaran-robotics.com/documentation/index.html.

9 http://www.cis.uni-muenchen.de/~schmid/tools/TreeTagger/.

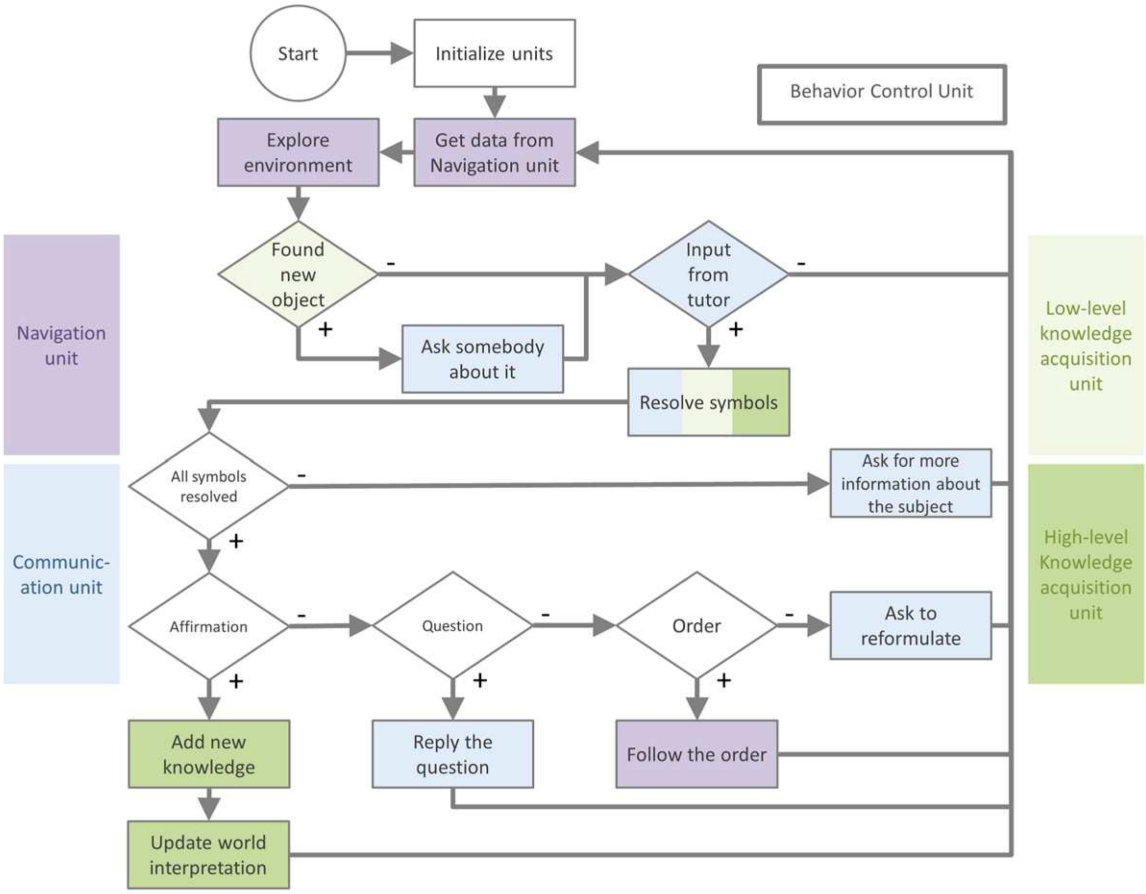

Fig. 8. A flowchart representing the Behavior Control Unit operation. Color of boxes indicates which of the four main units is participating in each particular step.

Table 1
A sample English phrase and its corresponding syntactic analysis output generated by TreeTagger.

Phrase:	Robots	are	our	friends
Tokens	NNS	VBP	PPS	NNS
Part-of-speech	noun, plural	VBP	possessive pron.	noun, plural
Lemma	robot	be	our	friend

noticed that it is not the core of the presented work. If in the presented work we used available software (e.g. TreeTagger) in order to provide an all-in-one realization description of the entire system and to show how the interaction contributes to enabling fully autonomous knowledge acquisition capabilities, this does not means that TreeTagger is the only possible option. In fact, another software, if it is more efficient or more appropriate (e.g. compatible) regarding robots architectural specificities could be used.

In spite of its usefulness, syntactic analysis only cannot provide sufficient information in a number of cases. Think about a situation, where a human says to the robot go to the office. Syntactic analysis may result into an order (go) and a place (office). This may be related by the robot to an entity on its map and the robot can plan its path to the office and finally get there. Consider on the other hand this counter-example. A human is pointing towards the office and says go there. With syntactic analysis done, the meaning of there is still difficult to resolve as it is unrelated to any physical entity of the world. This task of symbol resolving requires additional information. In this case it is the visual information about in which direction the speaker was pointing while speaking. This problem is addressed in works covering joint attention and situated speech, cf. [41]. We use a hand detection algorithm and couple it with the object detection algorithm in order to provide this supplementary information. When the robot is unable to resolve a particular phrase, it recourses to this joint attention mechanism as shown of the flow diagram on Fig. 9. Phrases the robot uses to communicate with the tutor are generated from templates that take keywords from the context of the communication as parameters. The approach is in some of its aspects inspired by ELIZA, the influential artificial agent processing natural language as a chatterbot described in [42].

6. Results

This section is dedicated to give the main results obtained during several experimentation. The goal of this section is not to give an exhaustive study but rather to show how we may improve autonomy of robots. The Section 6.1 describes an experiment where the robot uses its perceptual curiosity to explore freely an unknown environment and to learn different objects with their name. The Section 6.2 shows how the robot may acquire knowledge and use it to interpret the world. The Section 6.3 illustrate an example of the emergence of intelligent autonomous behavior. In this last experiment, the robot initiate a dialog in order to clarify an order given by human. All experiment are completed with video in order to show with sake realism the results.

6.1. Perceptual curiosity: free exploration and anchoring

In this experiment (see Video 1, online version available at http://dx.doi.org/10.1016/j.robot.2013.06.005), the system starts with a free exploration behavior. During this phase, the robot looks at around it and goes towards an objects when it found it. It stops when it is close to this object, then it starts a new observation. On Fig. 10, one picture is shown capturing the office

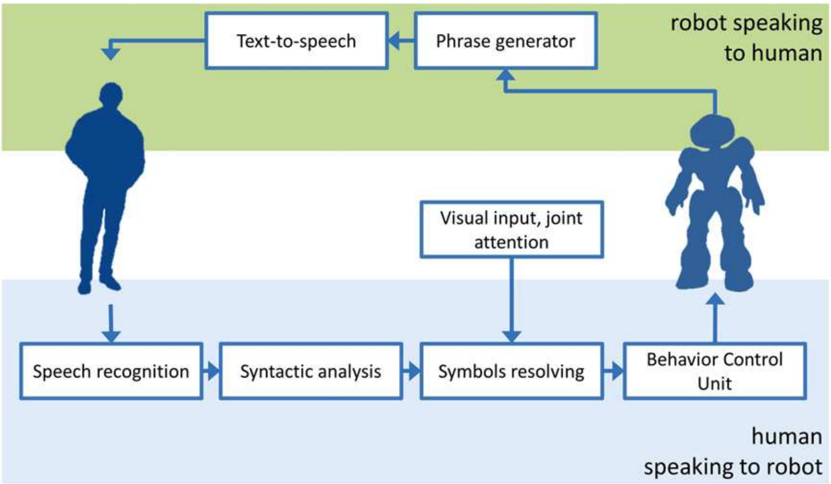

Fig. 9. Flow diagram of communication between a robot and a human which is used in this work.

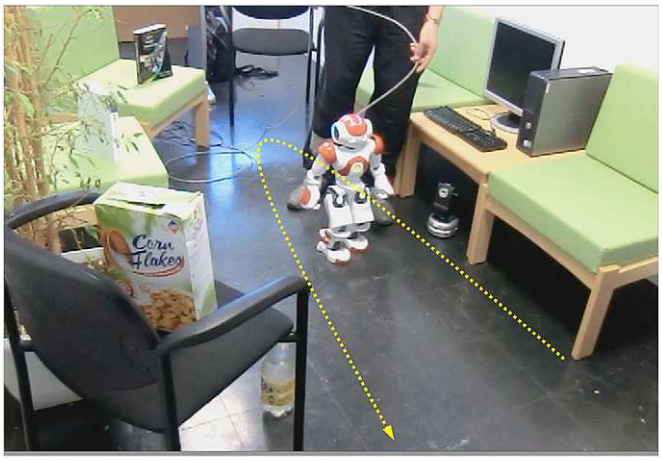

Fig. 10. Photo showing the robot in a real office environment. Some every-day objects like books, bottles and product boxes were added in order to enrich the environment by new visual stimuli.

Fig. 11. Example of objects discovered by the robot during the exploration.

room in which we have deployed NAO, the humanoid robot with our system. Different everyday objects have been distributed in the environment in different manners. During exploration, some of objects are discovered and learnt by the robot. On Fig. 11, some example of these discovered objects during exploration are shown. During the first part of this experiment, the robot need to use only the low level knowledge acquisition (see Section 5.1).

After this free exploration, the robot engages in a dialog with the tutor in order to learn more about objects it has seen during its exploration of the environment (see Fig. 12). In the second part of this experiment, the robot used the both low level and high level knowledge acquisition (see Section 5.1). The robot shares with the tutor its knowledge about the objects, which is merely limited to whether it had or had not seen them before during the exploration. The tutor in turn shares some of his much complete knowledge about the object with the robot. This dialog allow the robot and the tutor communicate on different subjects. An example of this dialog is given below:

– *Tutor*: Have you seen this?
– *Robot*: Yes, I have seen this. What is its name?
– *Tutor*: This is a first-aid-kit.
– *Robot*: Ok, I will remember that this is a first-aid-kit. (the robot learns the name)
– *Tutor*: Have you seen this?
– *Robot*: No, I have not seen this before. What is it? (the robot learns the appearance of this new object)
– *Tutor*: It is a teddy bear.
– *Robot*: Ok, I will remember that this is a teddy bear. (the robot learns the name).

This experiment shows how the robot can do connection between sensor data (visual perception) and symbols (names of each object). It is important to note that during interaction, the behavior of the robot is not fully passive. Effectively, according to the visual memory of the learnt objects, the robot may decided to learn only its name or the both its name and its visual appearance.

6.2. Perceptual and epistemic curiosity: autonomous knowledge acquisition

In this second experiment (see Video 2, online version available at http://dx.doi.org/10.1016/j.robot.2013.06.005), we have created an experimental scenarios to verify both the acquisition of knowledge and its use by the robot in order to validate the proposed approach in Section 4. The total of 25 every-day objects was collected for purposes of the experiment (see Fig. 13). They were randomly divided into two sets for training and for testing. Learning set objects were placed around the robot and then a human tutor pointed to each of them calling it by its name. Using its monocular color camera, the robot discovered and learned

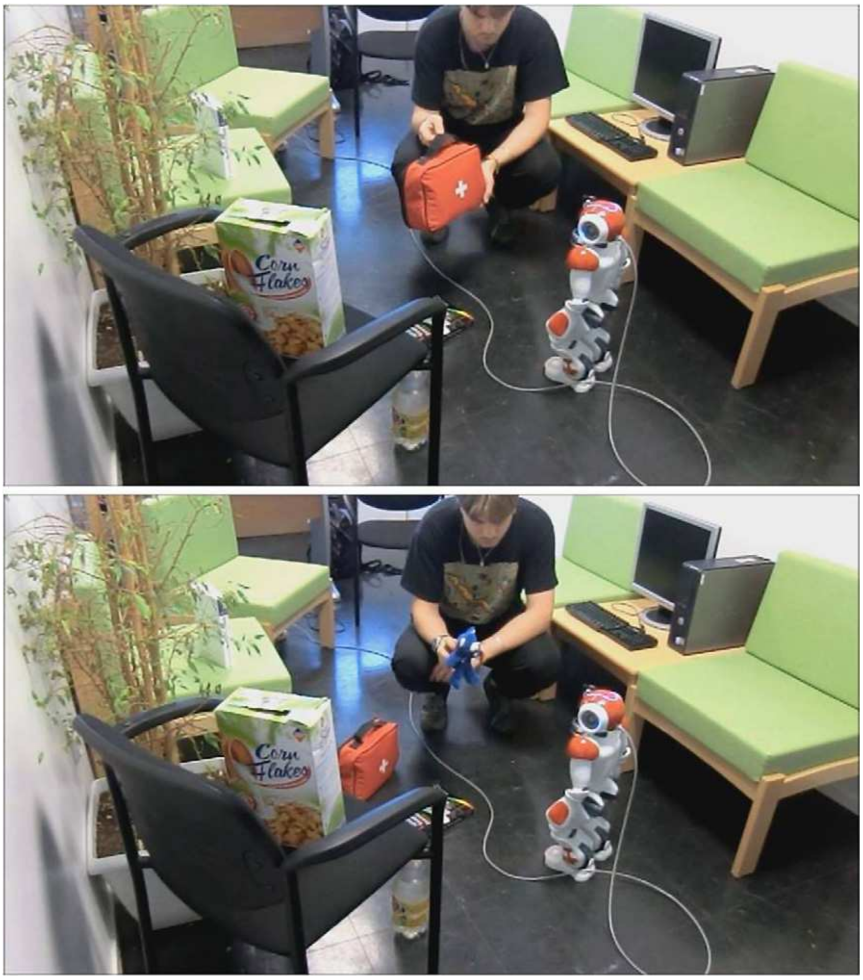

Fig. 12. Interaction of the tutor and the robot on subject of things the robot had or had not seen during its exploration: (a) learning the name of a previously seen object (a first-aid-kit), (b) learning the visual appearance and the name of a completely new object (a teddy-bear).

Fig. 13. Photo showing the robot with every-day objects used in the second experiment (right). Example of 4 objects and their associated utterances used during the learning stage (left).

the objects around him by the salient object detection approach. By detecting the movement of the tutors hand to achieve joint attention, the robot was able to determine what object the tutor is referring to and to learn its name. The tutor addressed to the robot in natural speech.

After learning the names of objects, those were presented randomly to the robot alongside of other objects. Then the tutor described each object in the view by saying for instance "The handbook is black and gray" or "the milk is blue and white". The robot was required to localize the object (e.g. handbook) among the presented objects based on the previous learning and to extract its color features along with the uttered information that the book was black and "gray". Then learning of the colors took place. To verify the results of learning, objects from the testing set were presented to the robot by the tutor, who then asked the robot to describe objects he was pointing towards (see Fig. 14). Using

Fig. 14. The tutor asked the robot to describe different objects. The robot describes the teddy bear like a white object, the apple like a red object.

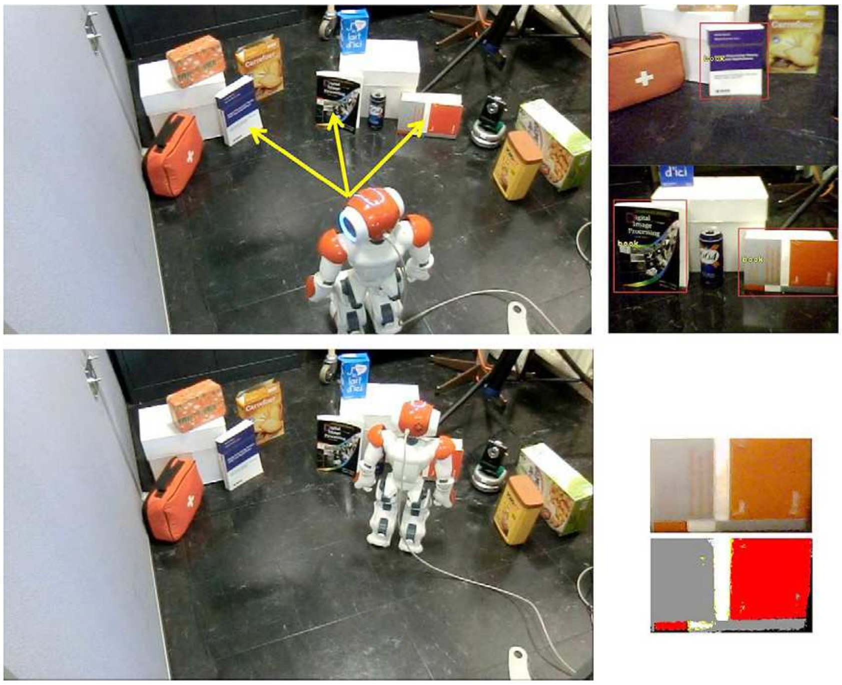

Fig. 15. Images from a video sequence showing the robot searching for the book and localizing several of them (top of picture). The robot receives an order to fetch the one which is red and interprets colors of all the detected books and finally reaches the desired one (bottom of the picture). The right column shows robot's camera view and visualization of color interpretation of the searched object. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the same joint attention scheme, as described before, the robot extracted the object in question, interpreted its appearance and spoke aloud the colors it believes the object contains.

It is important to noticed that the robot answers like a human could do it. For example, the robot describes the apple as a red object although the color of the apple was inhomogeneous. The similar remark may be done for the teddy bear which appear like white but which is in reality red and white.

6.3. Emergence of intelligent autonomous behavior: interaction and interpretation abilities

The last experimental scenario (Video 3, online version available at http://dx.doi.org/10.1016/j.robot.2013.06.005), we used involved distinguishing objects of the same class based on their color. First, several objects of the same class were presented to the robot. Then, the robot was asked to locate a particular object among all others given its color. The Fig. 15 shows an example of this kind of experiment where the robot have to find a book. Based on the previous learnt objects and colors, the tutor asked to fetch a book. After visually exploring the new surrounding environment, the robot see three books. At this stage, the robot does not have enough information to solve correctly this problem. Consequently, the robot asked more information and the tutor precise that it is the red book.

- *Tutor*: Go find the book!
- *Robot*: OK, I am searching for the book!
- *Robot*[after visually exploring the new surrounding environment]: I can see three books!
- *Tutor*: Get the red one!
- *Robot*[after walking towards the red book]: I am near the red book!

It must be pointed out that even if there is no fully red book in that environment, the robot has correctly interpreted the fact that the red book required by the human was the red and gray book. In comparison to conventional artificial recognition (e.g. Neural Network), the obtained behavior could seem as not obvious, however, it could be explained in view of the two kinds of curiosity mechanisms (i.e. low-level visual attention and high-level epistemic curiosity).

7. Conclusion

This paper presents an autonomous system for knowledge acquisition based on the notion of perceptual and epistemic curiosity. They drive the lower and the higher level of the present cognitive system in order to allow a mobile robot as well to learn in an autonomous manner new knowledge about the surrounding world as to use the acquired knowledge either to complete or to interpret items in its environment. Experimental results are provided and the approach is verified on a humanoid robot in a real-world environment using every-day objects. We have shown that using the described concept and issued overall architecture, the robot endowed with the presented cognitive system was able to successfully anchor the meaning of uttered words to its perception. Moreover, the third experiment focuses on a very interesting point which concerns the emergence of an autonomous behavior where the robot used its both interaction and interpretation abilities. Knowledge acquisition is motivated here by curiosity's mechanism, a high-level cognitive biologically inspired concept. Although usage of this concept in cognitive sciences is not new, the practice of such concept in cognitive robotics is very far from being obvious. In fact, in this article it is viewed from a new point of view, different from its usual use in existing works: acting in its different forms (perceptual vs. epistemic), curiosity drives both "reflexive" and "conscious" cognitive levels of the system. Through the two-tier architecture with a lower level (close to sensory data) and a higher level (close to semantic information) the cognitive system achieves the capacity of linking the perceptual experience with its high level (semantic) representation. It enables a humanoid robot endowed with this system to acquire knowledge in a manner that is inspired from young children learning and which makes the robot an active, enterprising partner in human–robot knowledge sharing, rather than a passive receptor. This represents a key step from human-supervised learning towards a fully autonomous and self-motivated knowledge acquisition in robots and ultimately, on a broader view, towards the full autonomy of robots.

Currently, our approach allows the robot to work with a single category or property at a time, (e.g. the color in utterances like "it is red"). We intend to pursue this work by extending it to allow for learning multiple categories (e.g. colors and shapes) at the same time and to distinguish, which of the used words are related to which category. In this case, there are two main problems to solve. The first one consists to investigating the extraction of appropriate features about what is (or is expected to be) learned. Among others, this first problem may concern, for example, the "shapes" learning by the robot where it is not easy to find appropriate features, regarding different interpretations and various usages that a human may associate to a same shape. An attractive slant to come to terms with this problem is to introduce co-evolution of several instances of the system described in this article, each of them dedicated to a different category (e.g. different features, different categories of objects, etc.). Another problem concerns the management of the memory. In fact, for a real application with a companion robot, it is important to manage correctly the memory of this robot on the long term. In this case, many points have to be solved: what is important (or pertinent) to store? What has to be remembered first in a given context? What could be forgotten and how restore the forgotten knowledge when it becomes pertinent? etc.

The "general intelligence" of the humans (e.g. humans' intrinsic intellect) reposes on human cognitive system as a basis. It is thus justified to say, that a machine system endowed with human-like intelligence will necessarily include an autonomous cognitive system as its basis, over which such an artificial intellect will operate on a higher functional level. With respect to the aforementioned, the long-term perspectives regarding the autonomous cognitive system presented in this article will focus on its integration to a system of larger scale realizing higher-level artificial intellectual functions (or tasks) in machines (such as mobile robots). There, it will play the role of an underlying system for machine-cognition and knowledge acquisition. This knowledge will be subsequently available as the basis for tasks proper for (machine) intelligence such as reasoning, decision making and an overall autonomy.

Appendix A. Coherent belief generation procedure

```
Initialisation:
int = new array of length |U| //interpretations of all utterances
rem_f = I //set remaining features to all observed features
while |rem_f| > 0 do
    //repeat while there are still unassigned features
    rem_u = U //set remaining utterances to all heard utterances
    while |rem_u| > 0 do
        //repeat while there are unassigned utterances
        //pick up a random utterance and construct its interpretation
        r = random utterance from rem_u
        if int[r] has no features assigned yet then
            //get all features observed in presence of the r-th utterance
            possible_f = features from rem_f observed in presence of r
            //get the feature the most dissimilar to any feature already
            //assigned to any of the interpretations
            f = feature from possible_f where
            |f − f_p| = max∀f_p ∈ int[r]
            add f to int[r]
            remove f from rem_f
        else
            //get all features observed in presence of the r-th utterance
            possible_f = features from rem_f observed in presence of r
            //get the feature the most similar to features from int[r]
            f = feature from possible_f where |f − f_p| = max∀f_p ∈ int
            //get average distance of f normalized to 0..1 scale
            dst = average distance |f − f_p| = max∀f_p ∈ int[r] from
            features in int[r]
            //probability of the feature being pertinent is proportional
            //to its distance to other features in int[r]
            if random number from 0to1 > dst then
                //consider the feature as pertinent in context of r
                add f to int[r]
            else
                //do nothing  consider the feature as impertinent
                remove f from rem_f
            end
            remove r from rem_u
        end
    end
end
```

Appendix B. Detection of ambiguities in a set of utterances

Under some conditions, a set of utterances on observations may be ambiguous, which would lead to multiple plausible interpretations of the world by the cognitive system although indeed only one would be conforming to the reality. In order to detect such ambiguities and to initiate the search for completing the missing information (i.e. to disambiguate the set), the following algorithm is used. U is the set of all sets of utterances given on all observations. D is the set of disambiguated utterances and A is the set of ambiguous utterances. We go through all combinations of any two members of A and test if:

1. their intersection produces one and only one utterance u_i,
2. their symmetric difference produce one and only one utterance u_i.

In the first case, it means that the only similarity in observations belonging to sets of utterances a and b is called u_i. In the second case, it means that the only difference in observations belonging to sets of utterances a and b is called u_i. Thus we have disambiguated the utterance u_i and we include it into D. When no further additions into D are possible, the set of ambiguous utterances A is given as the relative component of all utterances U and disambiguated utterances D.

Initialisation:
$U = \{U_1, ..., U_m\}$ // set to all sets of utterances
$D = 0$
while D *changes* **do**
  foreach (a from A)
  froeach (b from $(A - a)$)
   $a = (a - D)$ //remove already disambiguated utterances
   $b = (b - D)$
   if $(|a \cap b| = 1)$ $a \cap b \rightarrow D$ //intersection
   else if $(|a \triangle b|)$ $a \cup b \rightarrow D$ //symmetric difference
end
$A = (U - D)$
if $(|A| = D)$ no ambiguity
else ambiguity detected
//find any combination of sets of utterance from U

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